

PM007 – 29 November 2023

Update on PINNs

Application to Urban Wind Field Dispersion Studies

Some Updates to v3 - PM006

- 1) Number of neurons customizable from configuration file (PM003)
- 2) Type of activation function customizable (PM003)
- 3) Type of scaler customizable (PM003)
- 4) Custom points for physics loss (PM004)
- 5) Use of both optimizers (Adam first for an ansatz then LBFGS to fine tune solution) (PM004)
- 6) Option to overlay plots with quiver arrows in configuration file (PM005)
- 7) Option to plot for any angle in configuration file (PM005)
- 8) Option to plot Turbulent Viscosity (with directional arrows) (PM005)
- 9) Loss vs Epochs Plot (PM006)
- 10) RANS added to PINN (PM006)
- 11) Angles to add / remove from training dataset customizable (PM006)

Script Version v4

- 1) PINN is now completely customizable – customizable input and output parameters, batch normalization, dropout rate, neuron number, number of hidden layers – all options in the config file (PM007)
- 2) Saving of all the losses (not just the total loss) (PM007)
- 3) Plotting of loss vs epochs now automatic (PM007)
- 4) Boundary conditions – relaxed no slip condition included (PM007)
- 5) New angles included (PM007)
- 6) Smaller batch sizes (I disagree) – customizable from config file (PM007)

What is Batch Normalization?

Batch normalization is a technique used in training neural networks that standardizes the inputs to a layer for each mini-batch. This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks.

- 1) Normalization Process: In batch normalization, the inputs to a layer are normalized so that the mini-batch mean is 0 and the mini-batch variance is 1. This is similar to how input data is often normalized, but batch normalization does this for the inputs to each layer within the network.
- 2) Improves Gradient Flow: It can help mitigate the problem of vanishing or exploding gradients, especially in deep networks.
- 3) Allows Higher Learning Rates: By stabilizing the distribution of the inputs to layers throughout training, it allows for the use of higher learning rates, potentially speeding up the training process.
- 4) Reduces Overfitting: It can have a regularization effect, reducing overfitting to some extent. This is because it adds a small amount of noise to the inputs within each layer during training.

Implementation Details:

- 5) Learnable Parameters: In addition to normalizing the inputs, batch normalization also introduces two learnable parameters per feature: one to scale and another to shift the normalized value. This is to ensure that the normalization process doesn't nullify the capacity of the layer to represent the input data.
- 6) During Training: During the training phase, the mean and variance used for normalization are computed on the mini-batch.
- 7) During Testing: During the testing phase, the mean and variance are estimated from the entire training dataset.
- 8) Usage in Neural Networks: Batch normalization is typically applied after the linear (or convolutional) operations and before the non-linear activation function (like ReLU) in a network layer.
- 9) By making each layer's inputs more predictable, batch normalization helps to stabilize the training process of deep neural networks.

What is Dropout Rate?

Dropout is a regularization technique used in neural networks to prevent overfitting. The dropout rate is a hyperparameter that determines the probability at which units (neurons) in the neural network are randomly dropped (i.e., temporarily removed) during training.

- 1) During training, at each iteration, individual neurons are randomly "dropped out" of the network with a probability equal to the dropout rate. This means they are temporarily ignored during that forward and backward pass.
- 2) The neurons that are dropped don't contribute to the forward pass and don't participate in backpropagation. As a result, their contribution to the learning process is temporarily removed.
- 3) The dropout rate is a fraction between 0 and 1. For example, a dropout rate of 0.5 means there is a 50% chance that each neuron will be dropped during a training iteration.
- 4) Choosing the right dropout rate is crucial. Too high a rate might lead to underfitting, as too much information is lost. Too low a rate might be ineffective in preventing overfitting.
- 5) Reduces Overfitting: By randomly dropping neurons, the network becomes less sensitive to the specific weights of neurons. This leads to a network that is capable of better generalization and is less likely to overfit to the training data.
- 6) Ensemble Effect: Dropout can be seen as a way of training a large ensemble of neural networks with shared weights. At test time, it's like averaging the predictions from this ensemble, which often leads to better performance.
- 7) Dropout is usually applied to fully connected layers or dense layers in a network, though it can be used with convolutional layers as well.
- 8) During inference or testing, dropout is not used; all neurons are active, but their outputs are scaled down by the dropout rate to balance the fact that more neurons are active than during training.
- 9) In summary, dropout randomly silences a subset of neurons in each training iteration, which helps the network to generalize better, making it more robust to unseen data. This technique is particularly useful in large neural networks to mitigate the risk of overfitting.

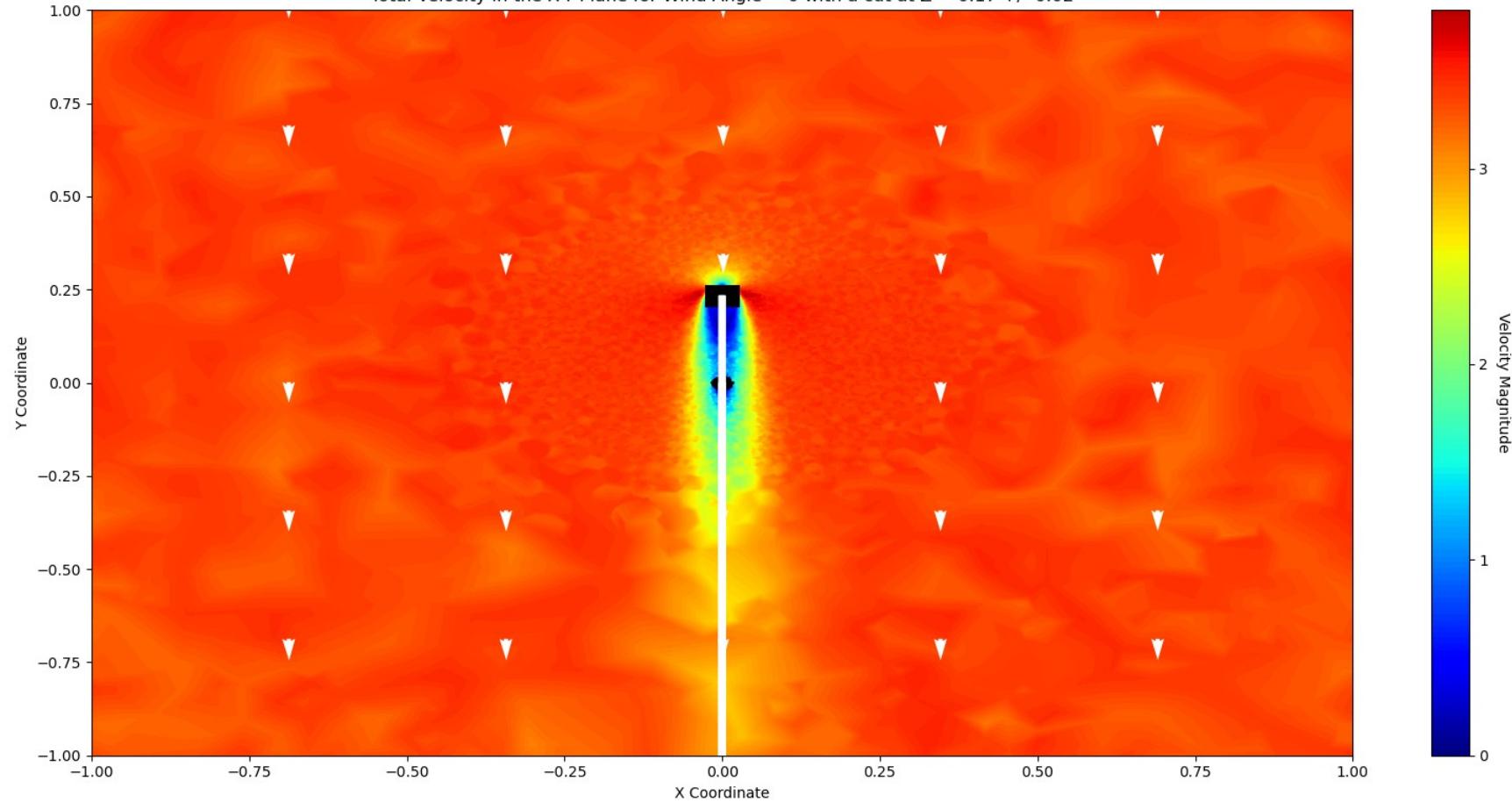
Why a smaller batch size?

The paper "On Large-Batch Training for Deep Learning: Generalization Gap and Sharp Minima" by Tang et al., investigates the effects of large-batch training in deep learning and its impact on model generalization.

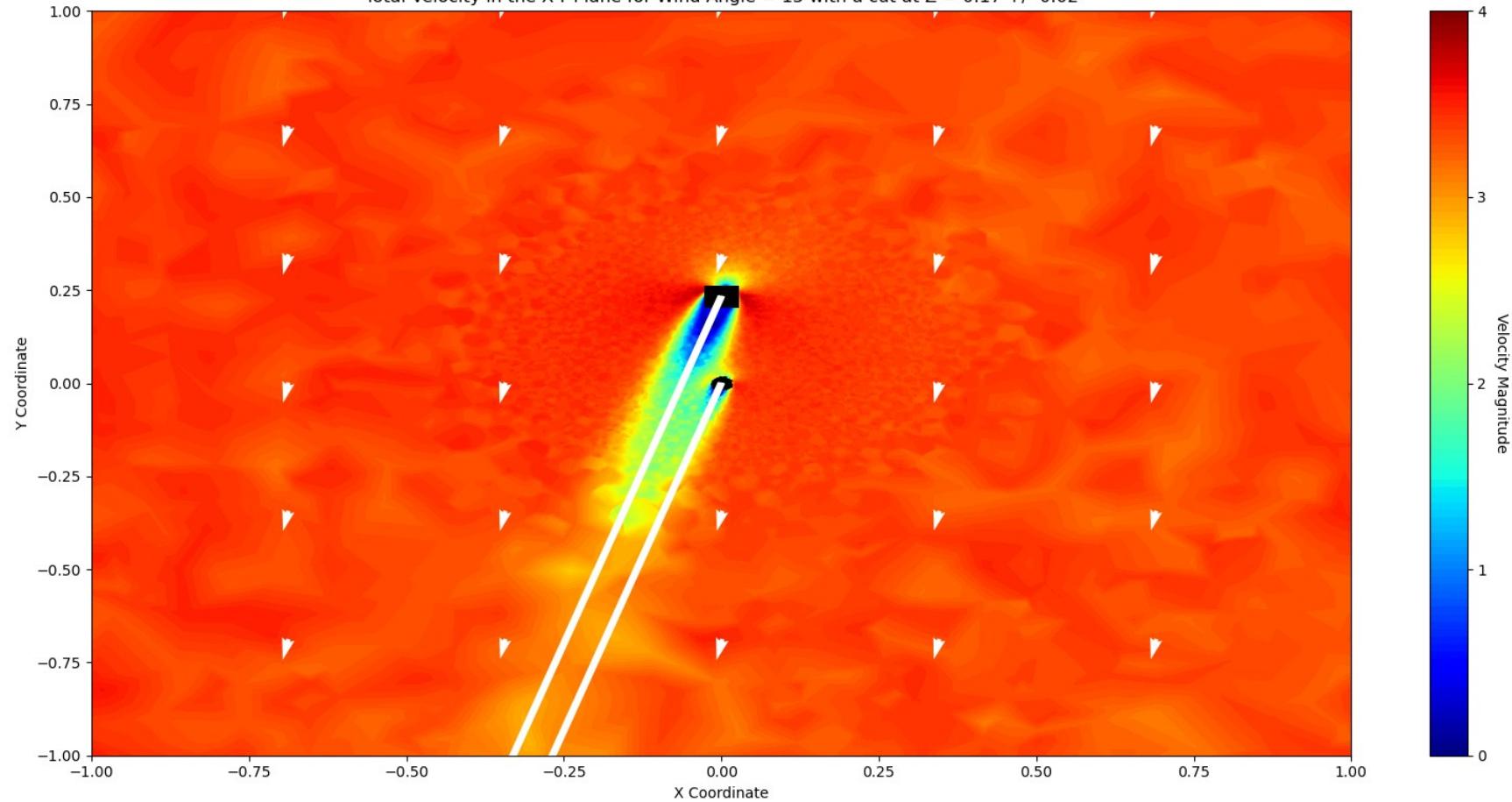
- 1) Issue Addressed: The paper investigates why large-batch methods in deep learning (using more data points per training iteration) lead to worse model generalization compared to small-batch methods.
- 2) Main Finding: Large-batch methods tend to converge to sharp minimizers of the training and testing functions, which leads to poor generalization. Small-batch methods, in contrast, converge to flat minimizers, which generalize better.
- 3) Proposed Strategies: Several strategies are discussed to mitigate the generalization gap in large-batch methods.
- 4) Context: Deep Learning models are foundational in many tasks like computer vision and natural language processing. Training these models involves non-convex optimization, typically using Stochastic Gradient Descent (SGD) and its variants.
- 5) Problem with Large Batches: Increasing the batch size for training, which seems a natural way to speed up the process, actually leads to a decrease in the model's performance on test data, known as the generalization gap.
- 6) Generalization Gap: The paper confirms through experiments that large-batch methods have a generalization gap compared to small-batch methods.
- 7) Nature of Minimizers: Sharp minimizers found by large-batch methods are characterized by a large number of large positive eigenvalues in the Hessian matrix, leading to poor generalization. Small-batch methods find flat minimizers with many small eigenvalues.
- 8) Numerical Experiments: The paper presents extensive numerical experiments using different network architectures and datasets to support these observations.
- 9) Threshold of Batch Size: There is a threshold batch size after which increasing it leads to a sharp decline in test accuracy. (Recommended between 32 and 512, in powers of 2)
- 10) Role of Gradient Noise: The inherent noise in gradient estimation in small-batch methods helps in avoiding sharp minimizers and promotes convergence to flat minimizers.
- 11) The paper suggests that the convergence to sharp minimizers is a key reason behind the poor generalization of large-batch methods.
- 12) The strategies tested provided some improvements but did not completely eliminate the issue.
- 13) The study leaves open questions about designing neural network architectures and training methods that are more compatible with large-batch training.
- 14) This research highlights a critical challenge in optimizing deep learning training processes, particularly regarding batch size and its impact on the model's ability to generalize. It underscores the need for further research in developing effective large-batch training techniques that do not compromise generalization.

Pure Data Plots – New Angles (Total Velocity)

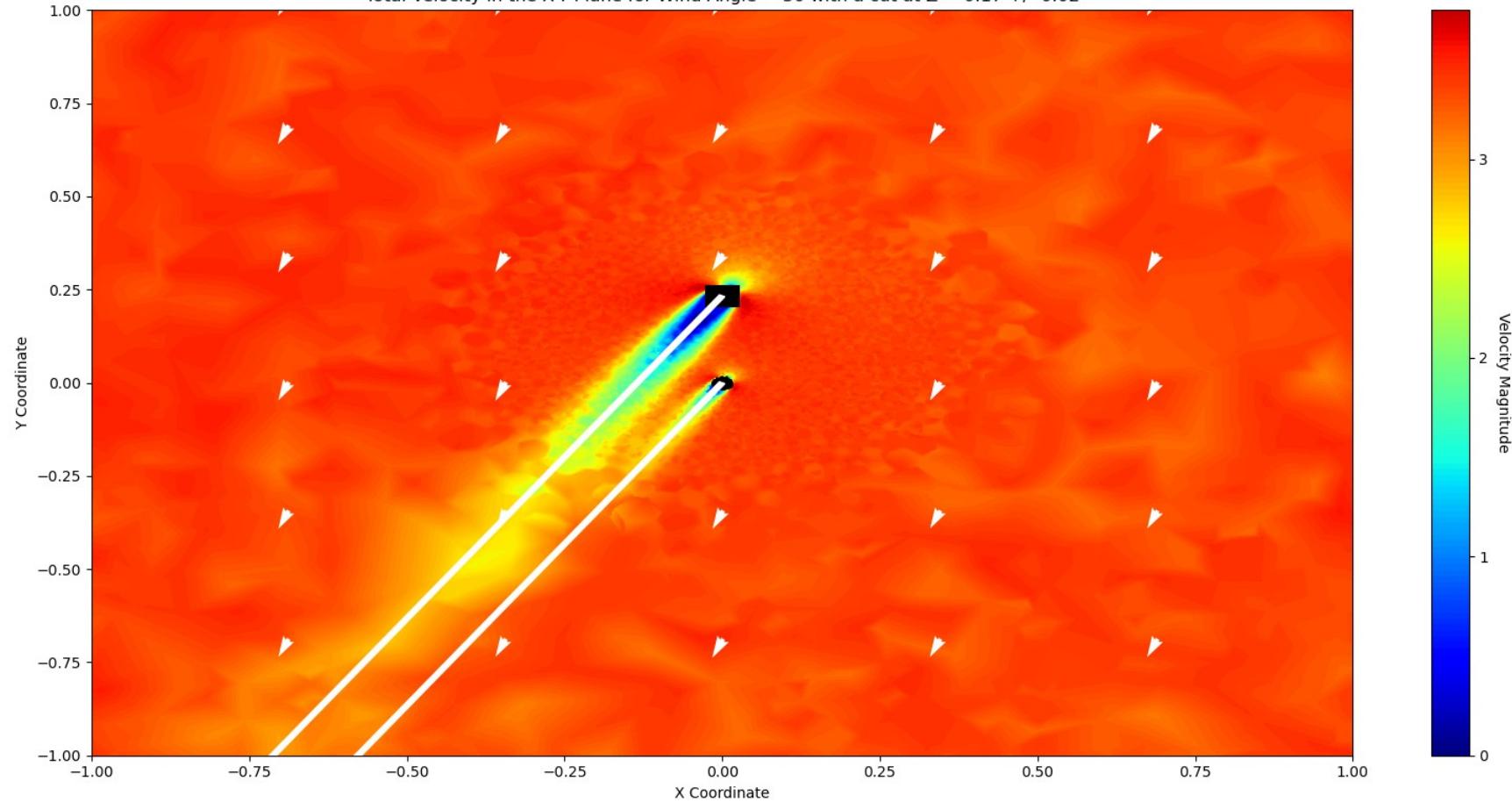
Total Velocity in the X-Y Plane for Wind Angle = 0 with a cut at $Z = 0.17 \pm 0.02$



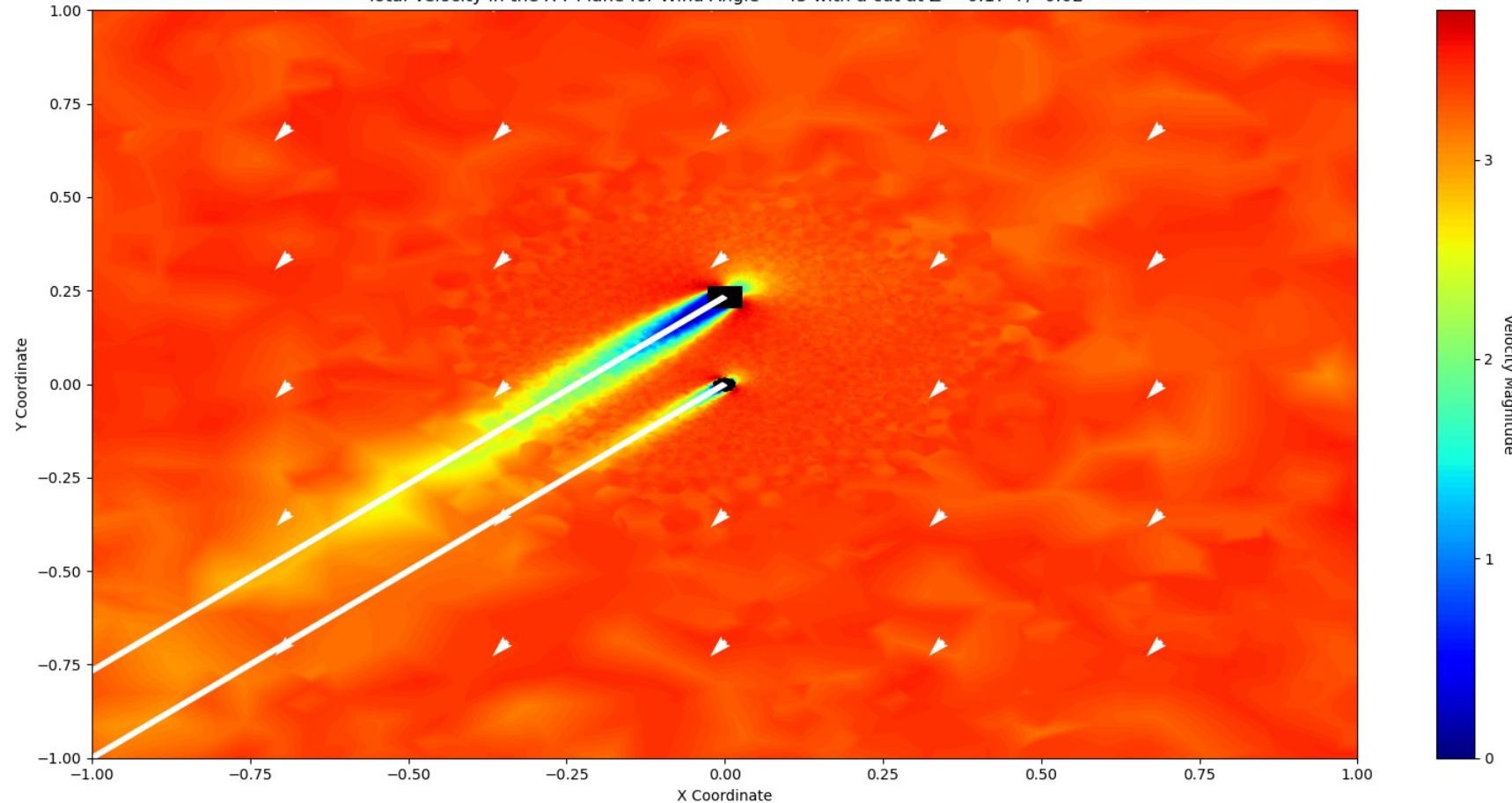
Total Velocity in the X-Y Plane for Wind Angle = 15 with a cut at Z = 0.17 +/- 0.02



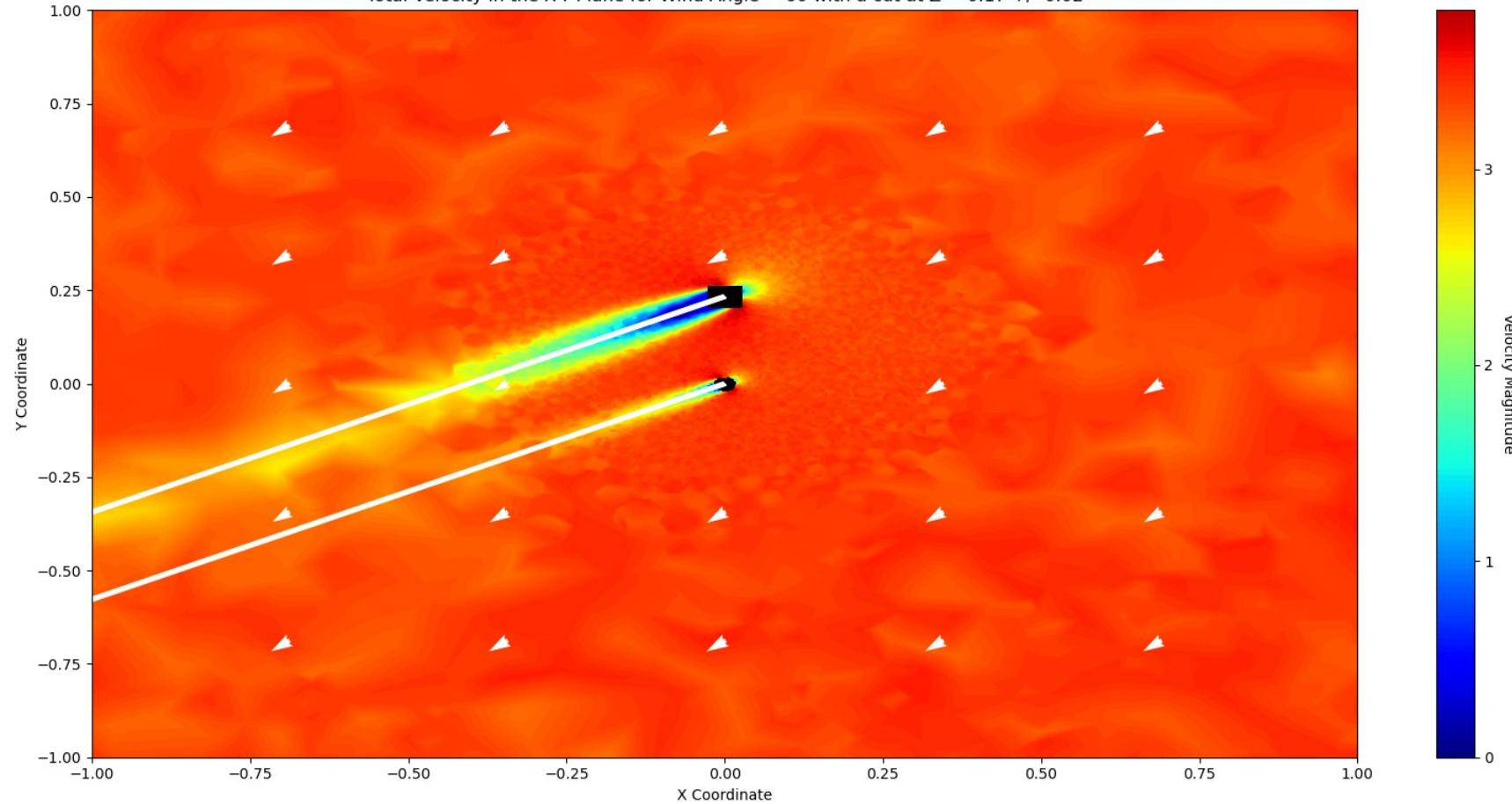
Total Velocity in the X-Y Plane for Wind Angle = 30 with a cut at Z = 0.17 +/- 0.02



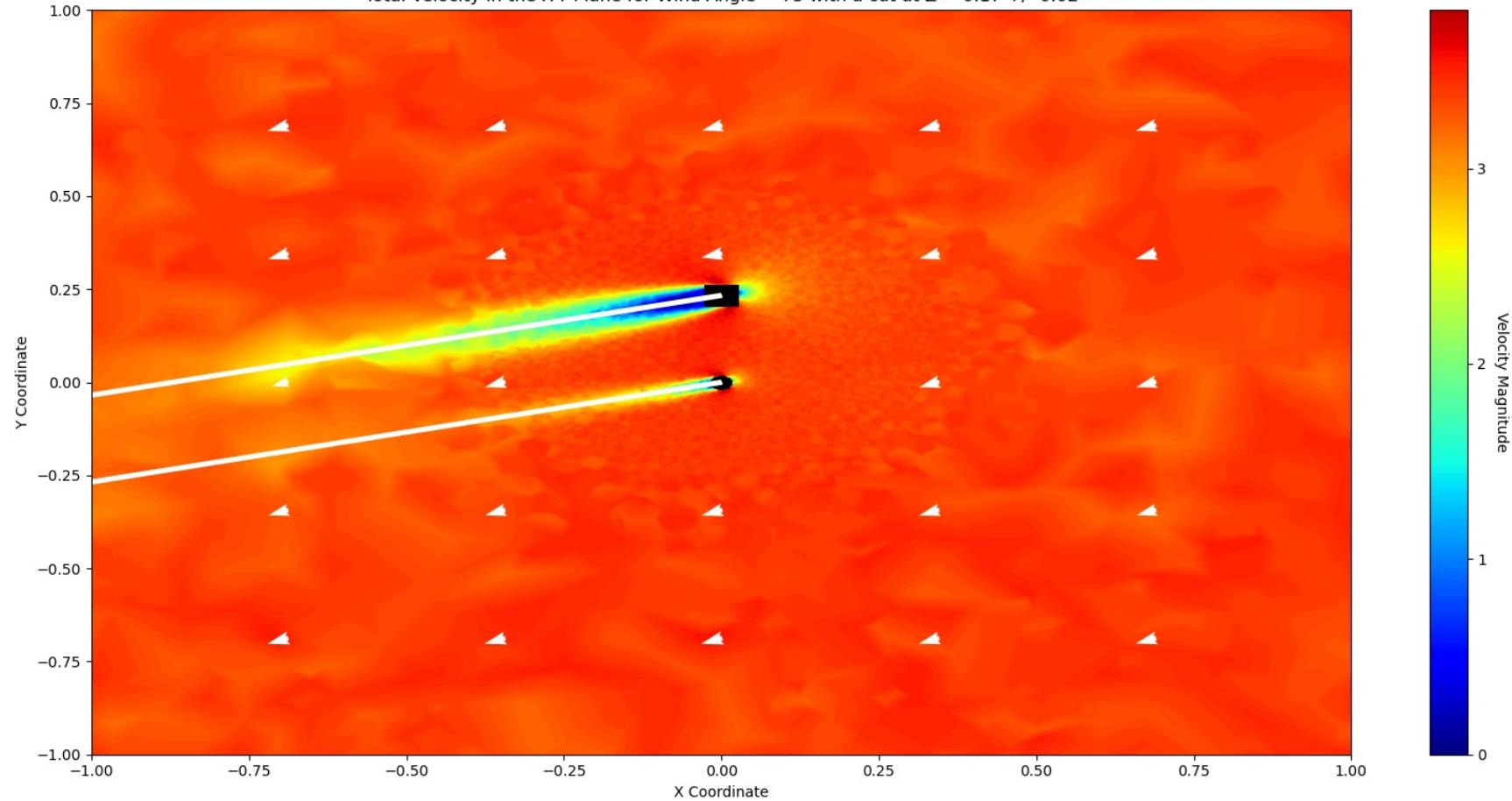
Total Velocity in the X-Y Plane for Wind Angle = 45 with a cut at Z = 0.17 +/- 0.02



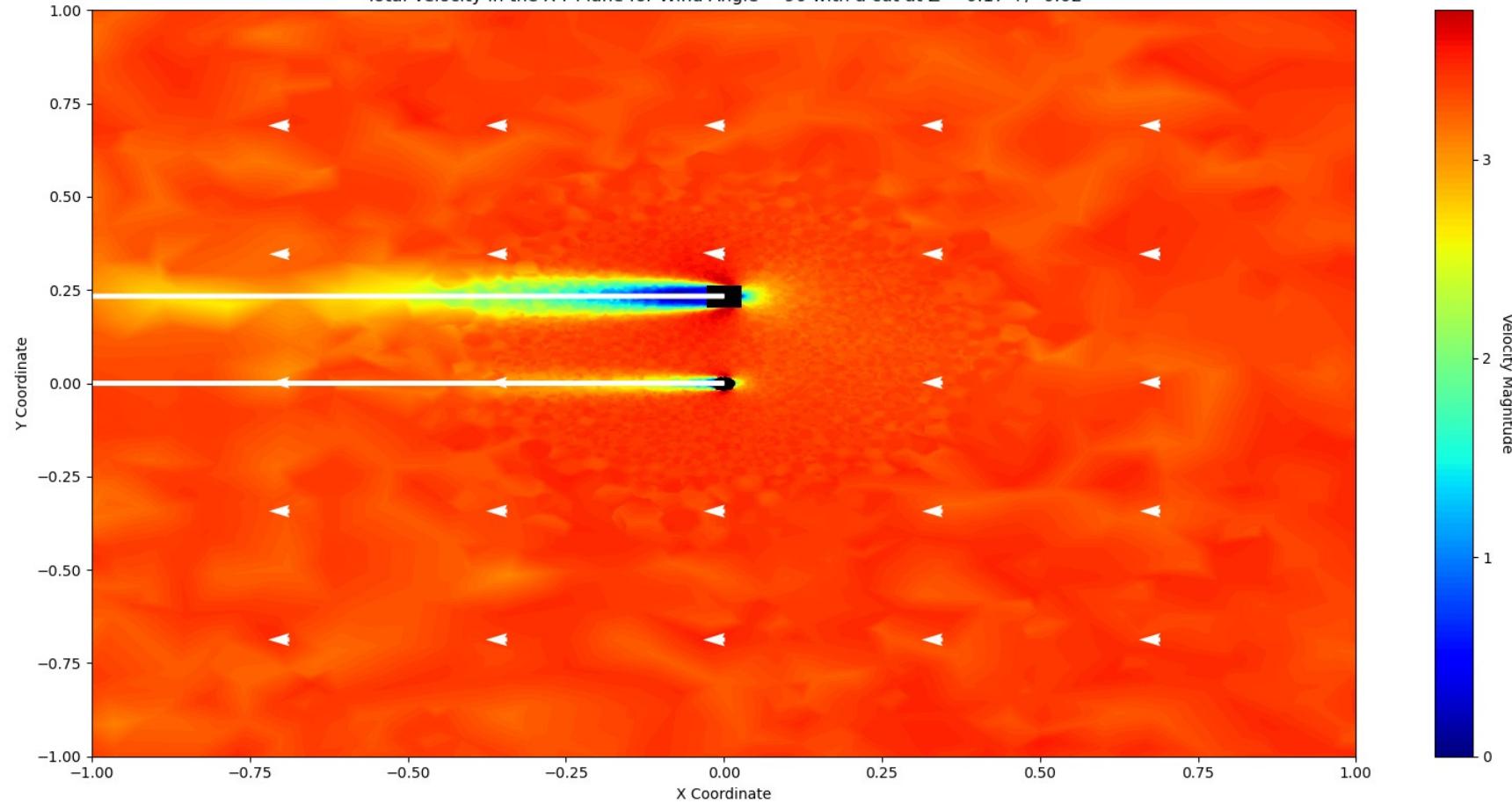
Total Velocity in the X-Y Plane for Wind Angle = 60 with a cut at Z = 0.17 +/- 0.02



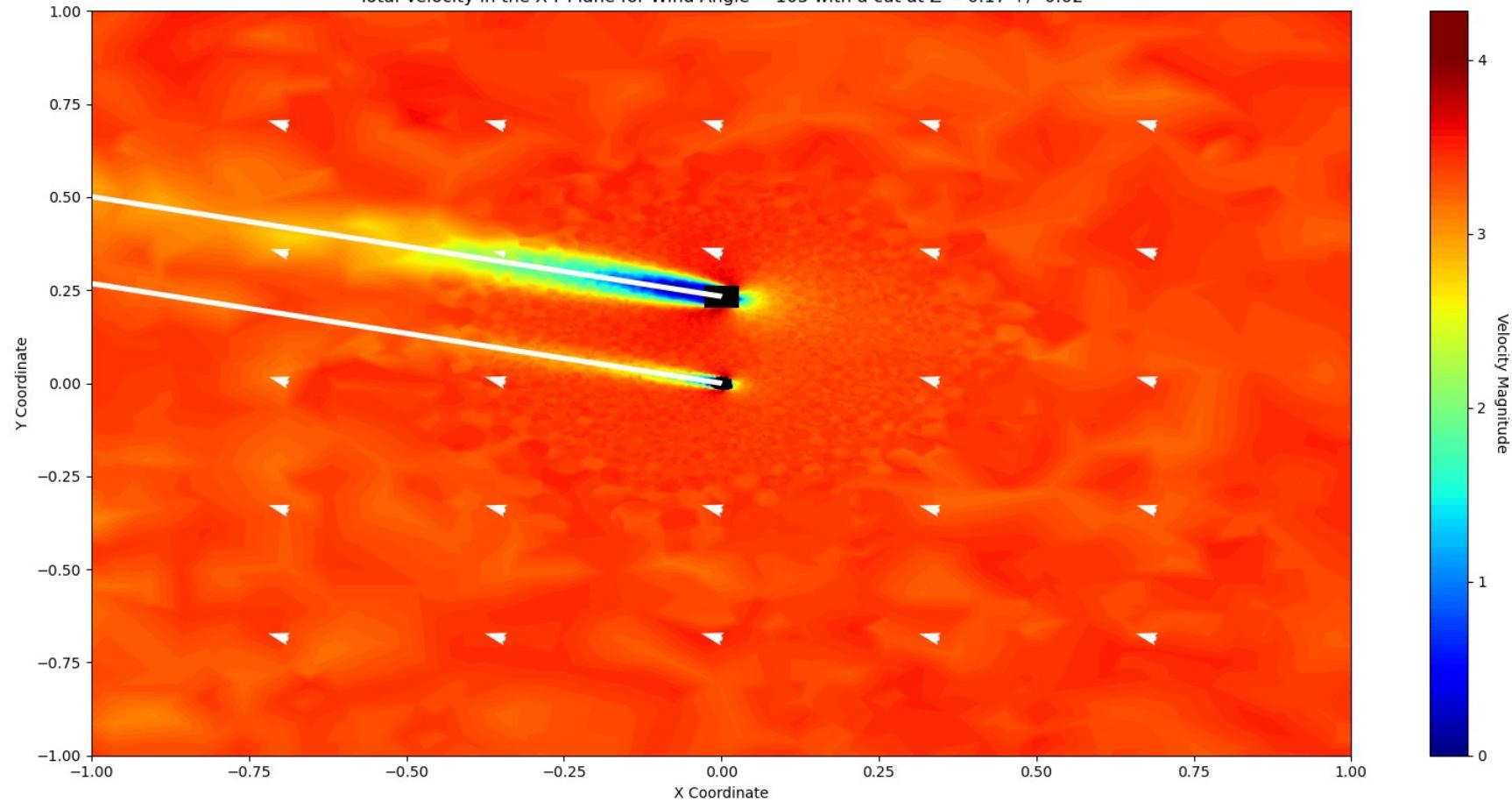
Total Velocity in the X-Y Plane for Wind Angle = 75 with a cut at Z = 0.17 +/- 0.02



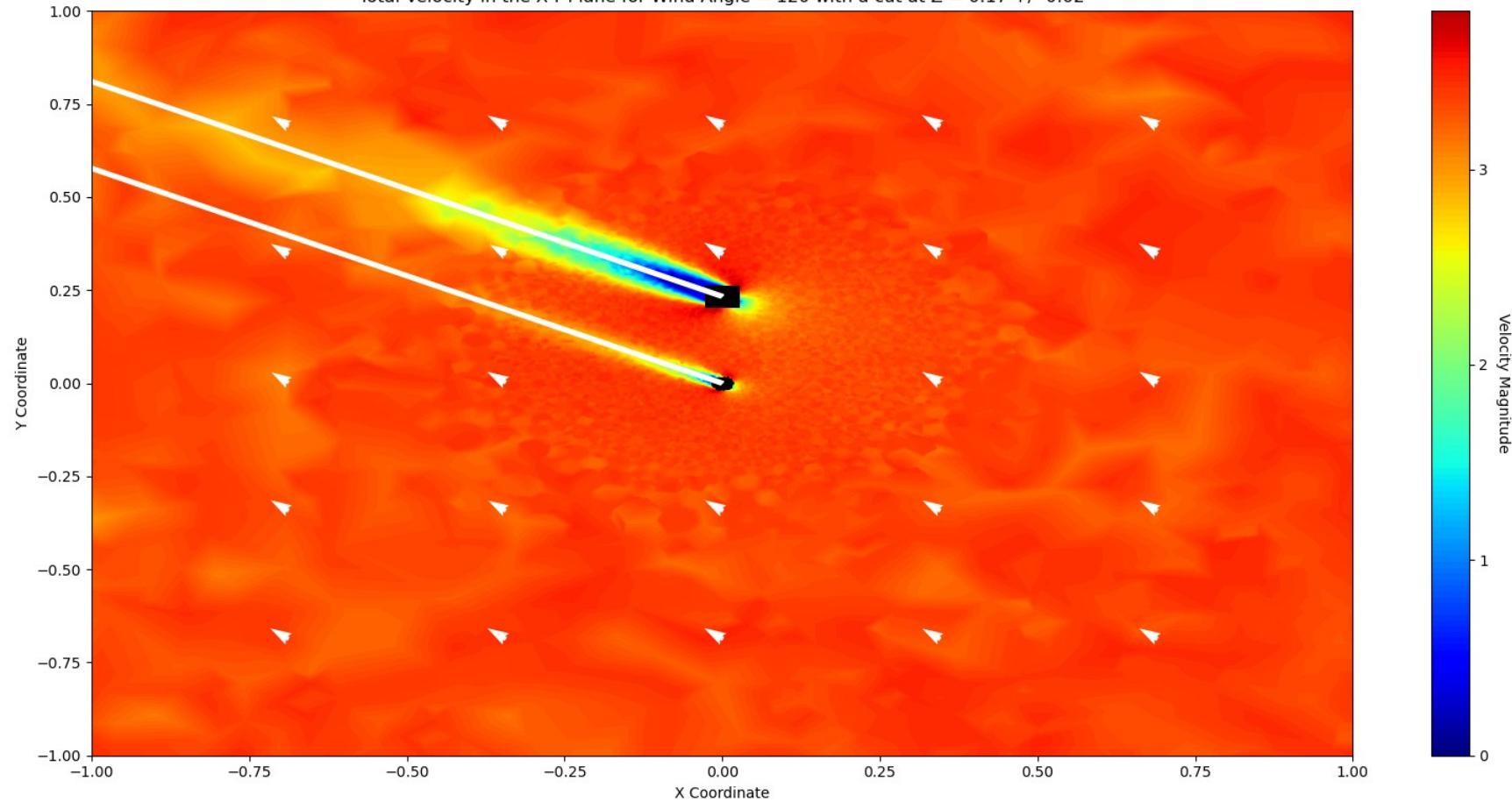
Total Velocity in the X-Y Plane for Wind Angle = 90 with a cut at Z = 0.17 +/- 0.02



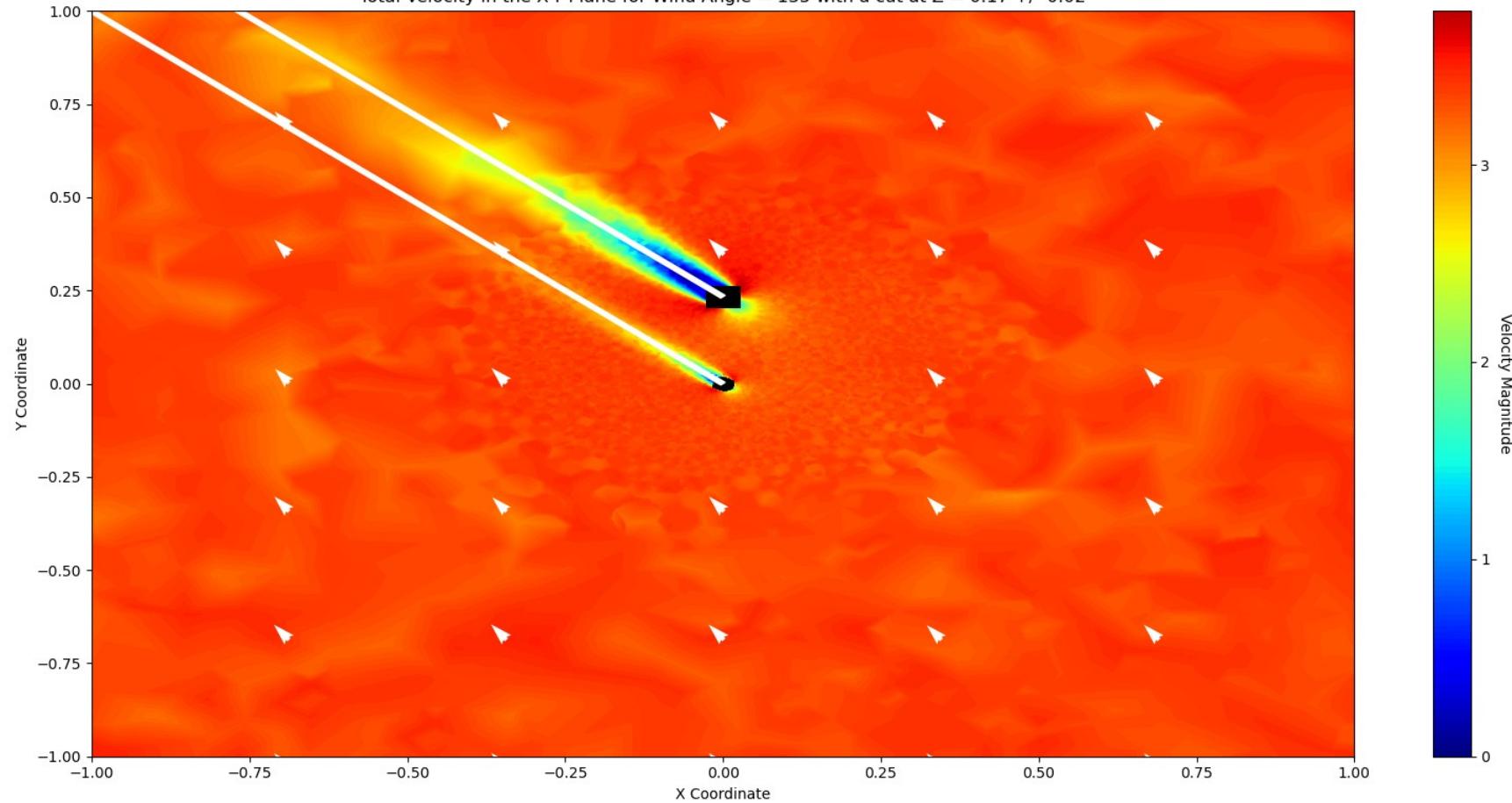
Total Velocity in the X-Y Plane for Wind Angle = 105 with a cut at Z = 0.17 +/- 0.02



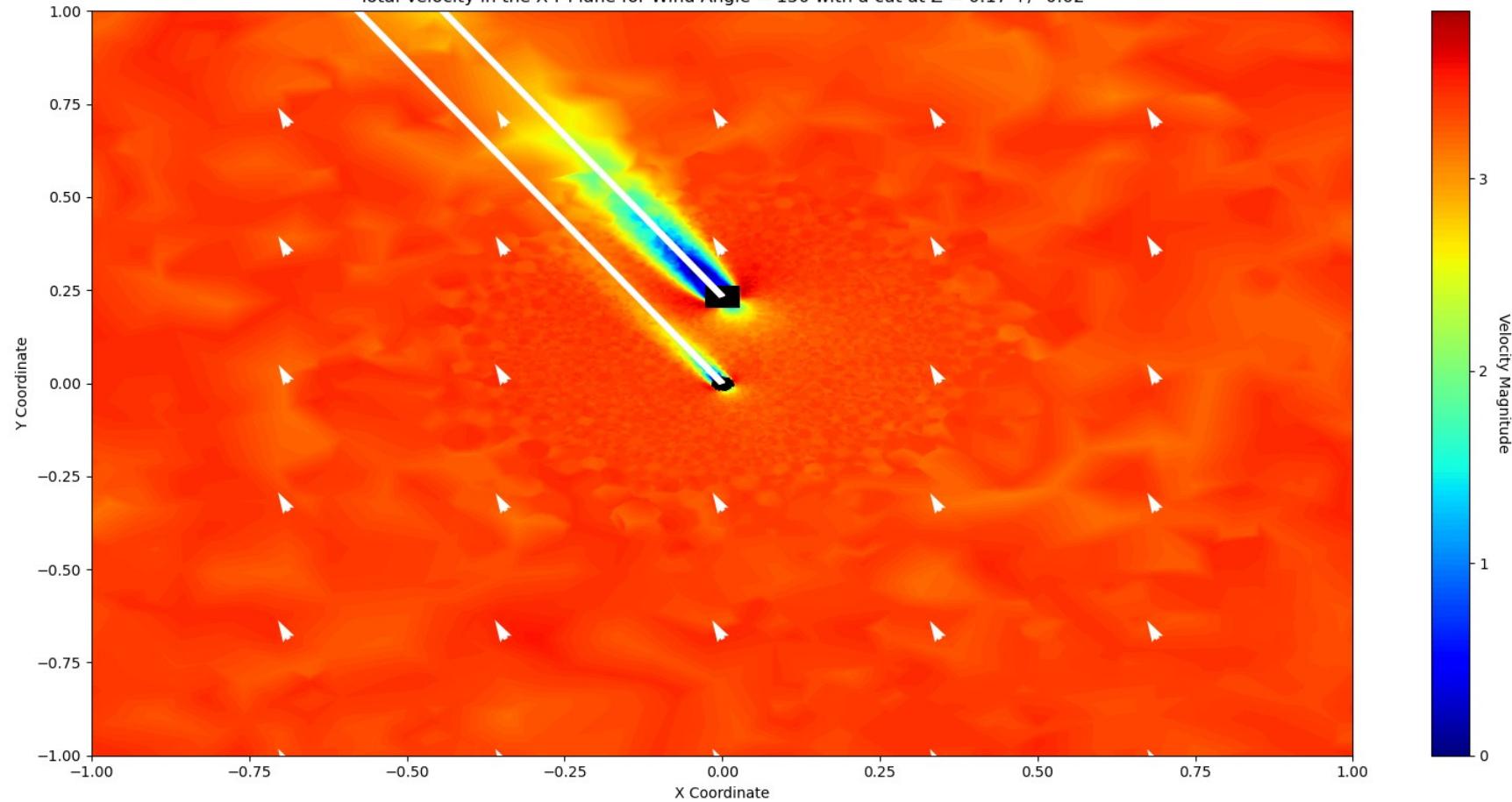
Total Velocity in the X-Y Plane for Wind Angle = 120 with a cut at Z = 0.17 +/- 0.02



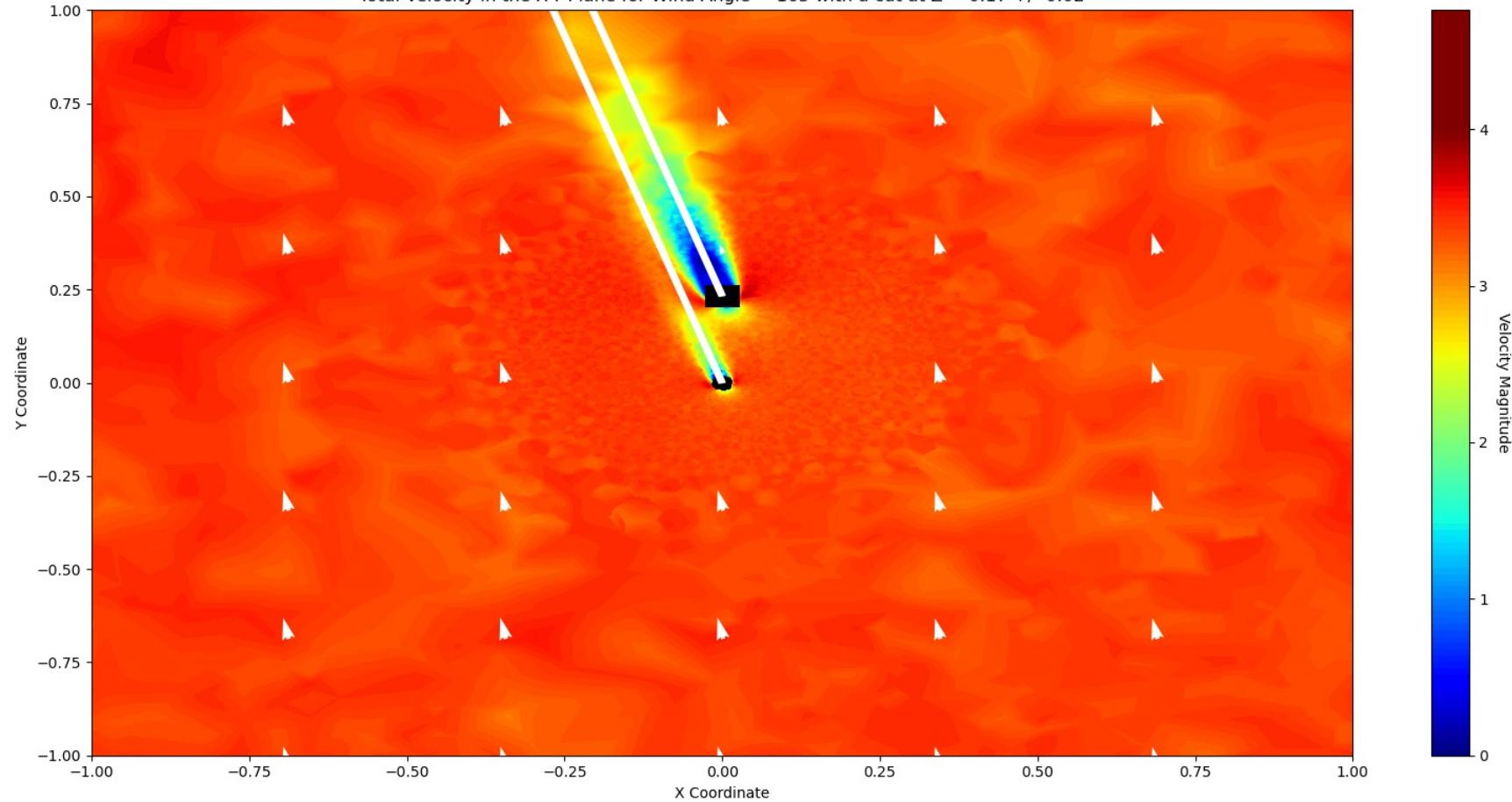
Total Velocity in the X-Y Plane for Wind Angle = 135 with a cut at Z = 0.17 +/- 0.02



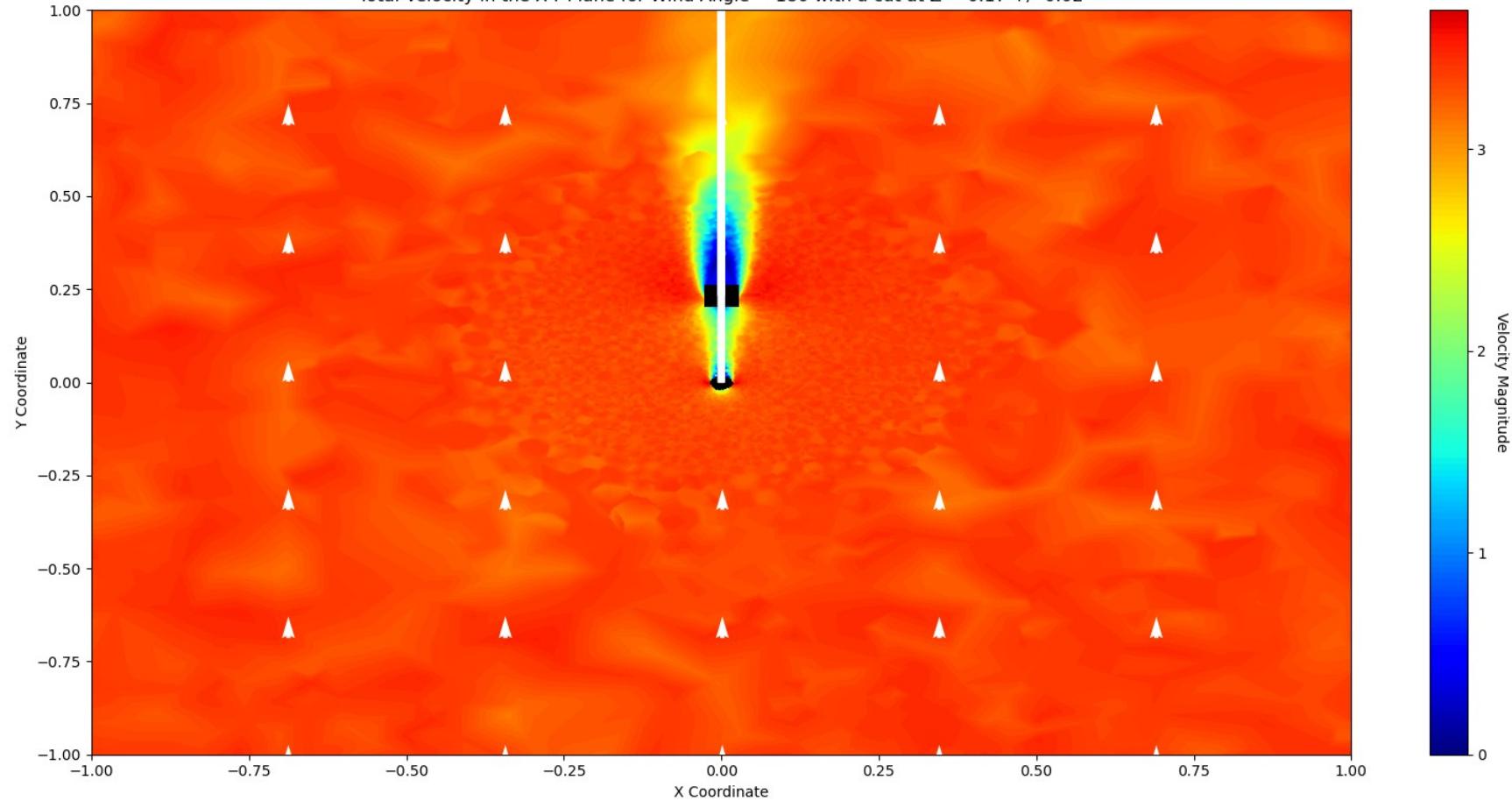
Total Velocity in the X-Y Plane for Wind Angle = 150 with a cut at Z = 0.17 +/- 0.02



Total Velocity in the X-Y Plane for Wind Angle = 165 with a cut at Z = 0.17 +/- 0.02

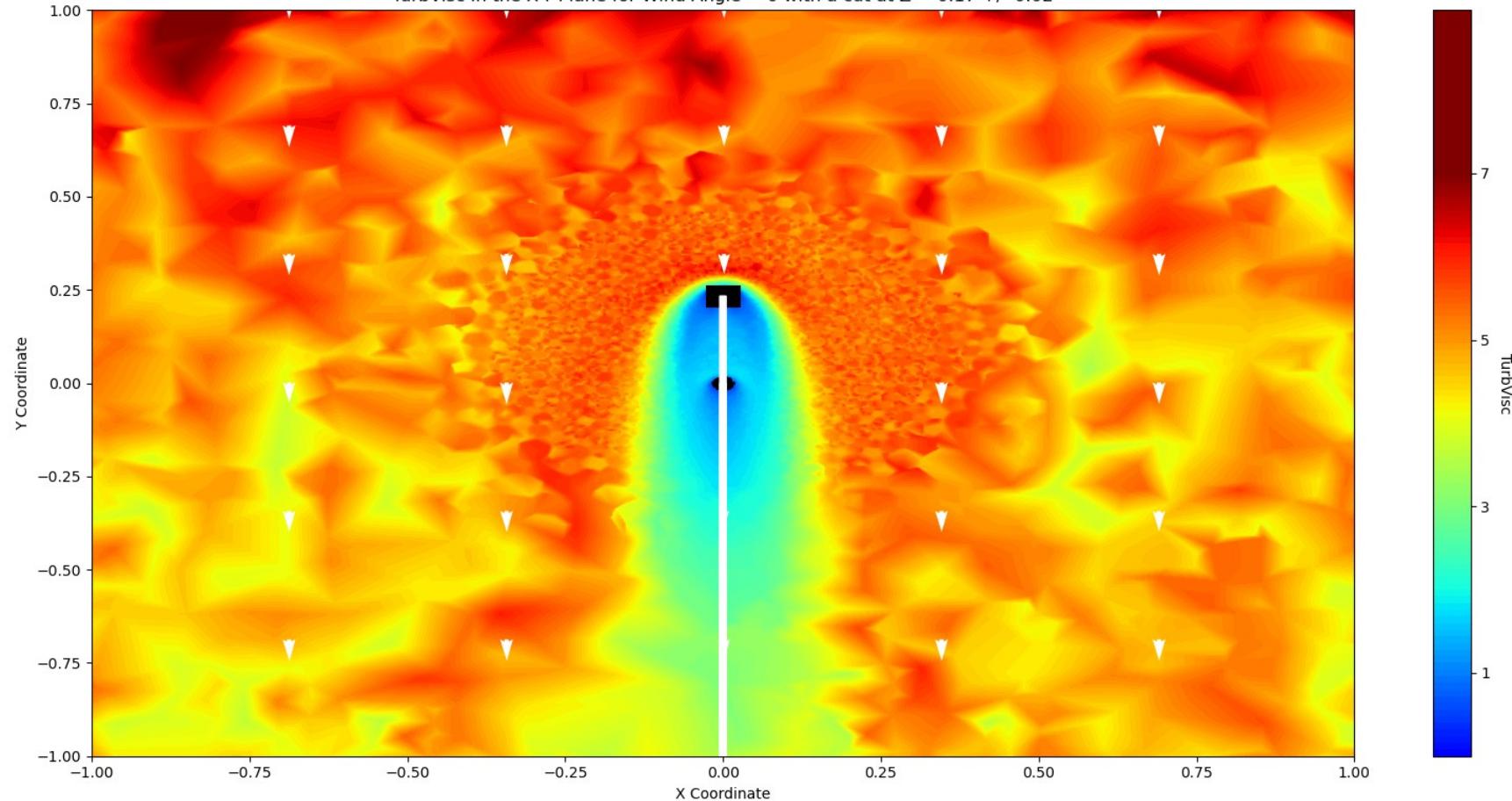


Total Velocity in the X-Y Plane for Wind Angle = 180 with a cut at Z = 0.17 +/- 0.02

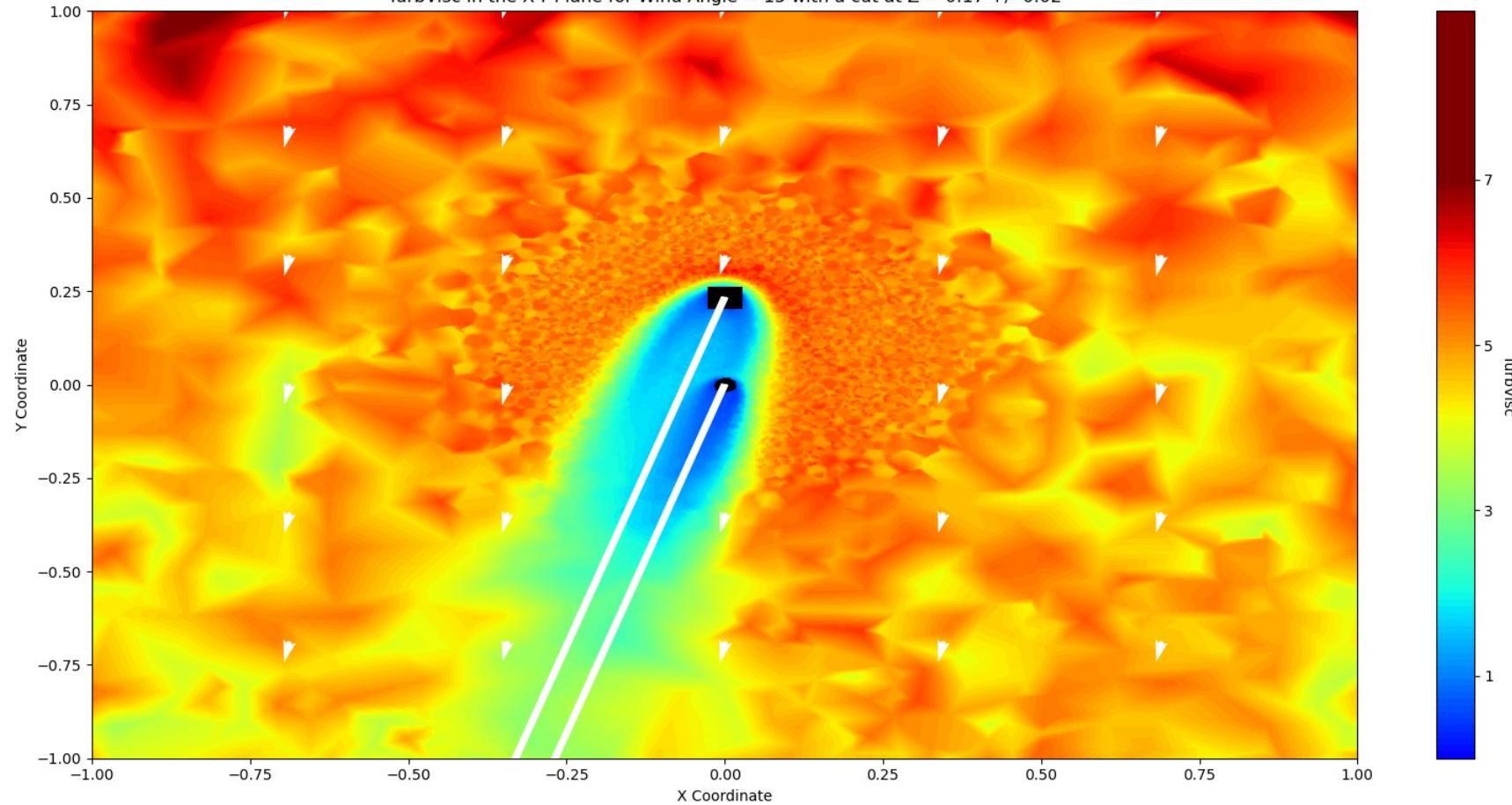


Pure Data Plots – New Angles (TurbVisc)

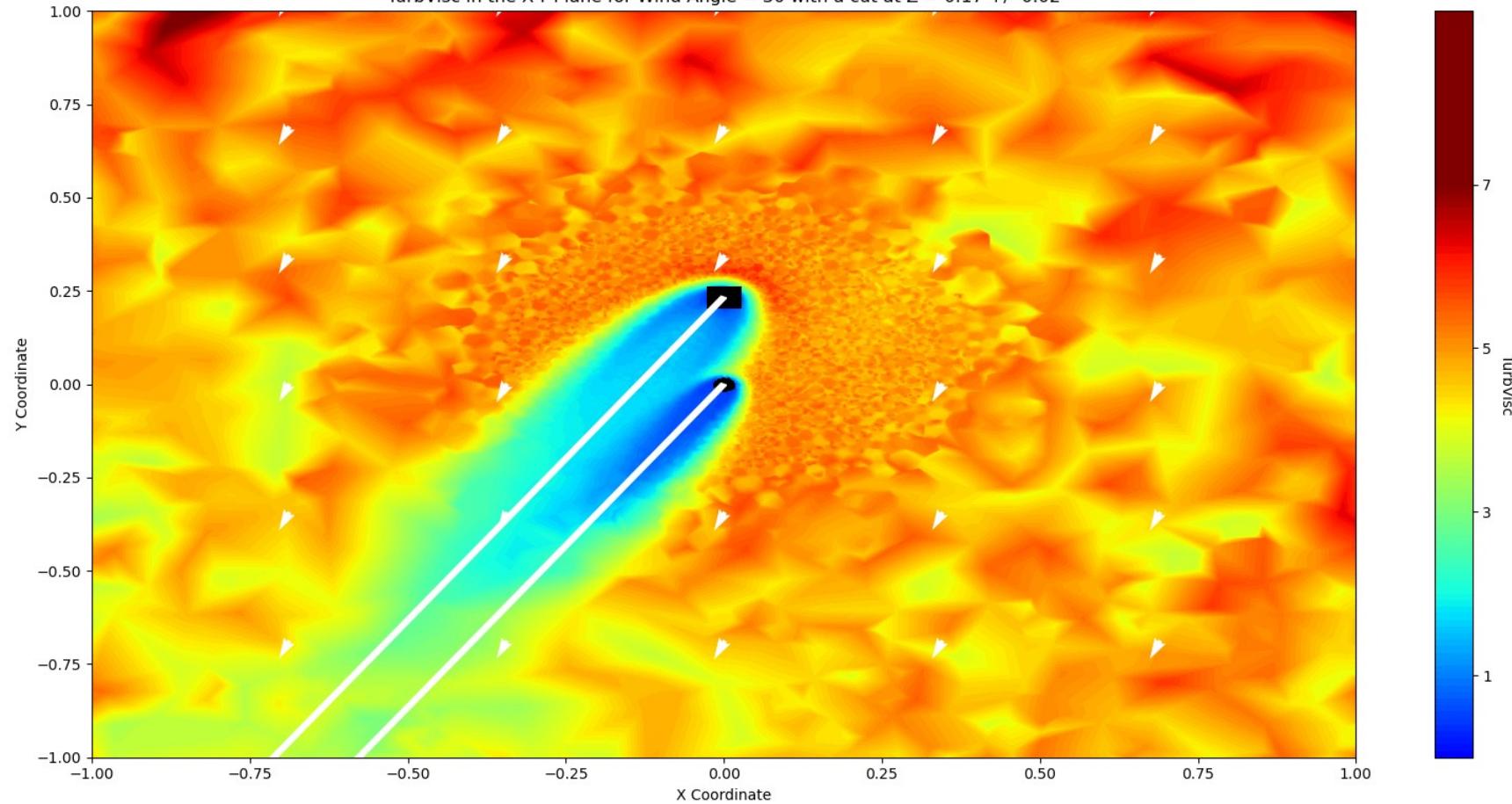
TurbVisc in the X-Y Plane for Wind Angle = 0 with a cut at Z = 0.17 +/- 0.02



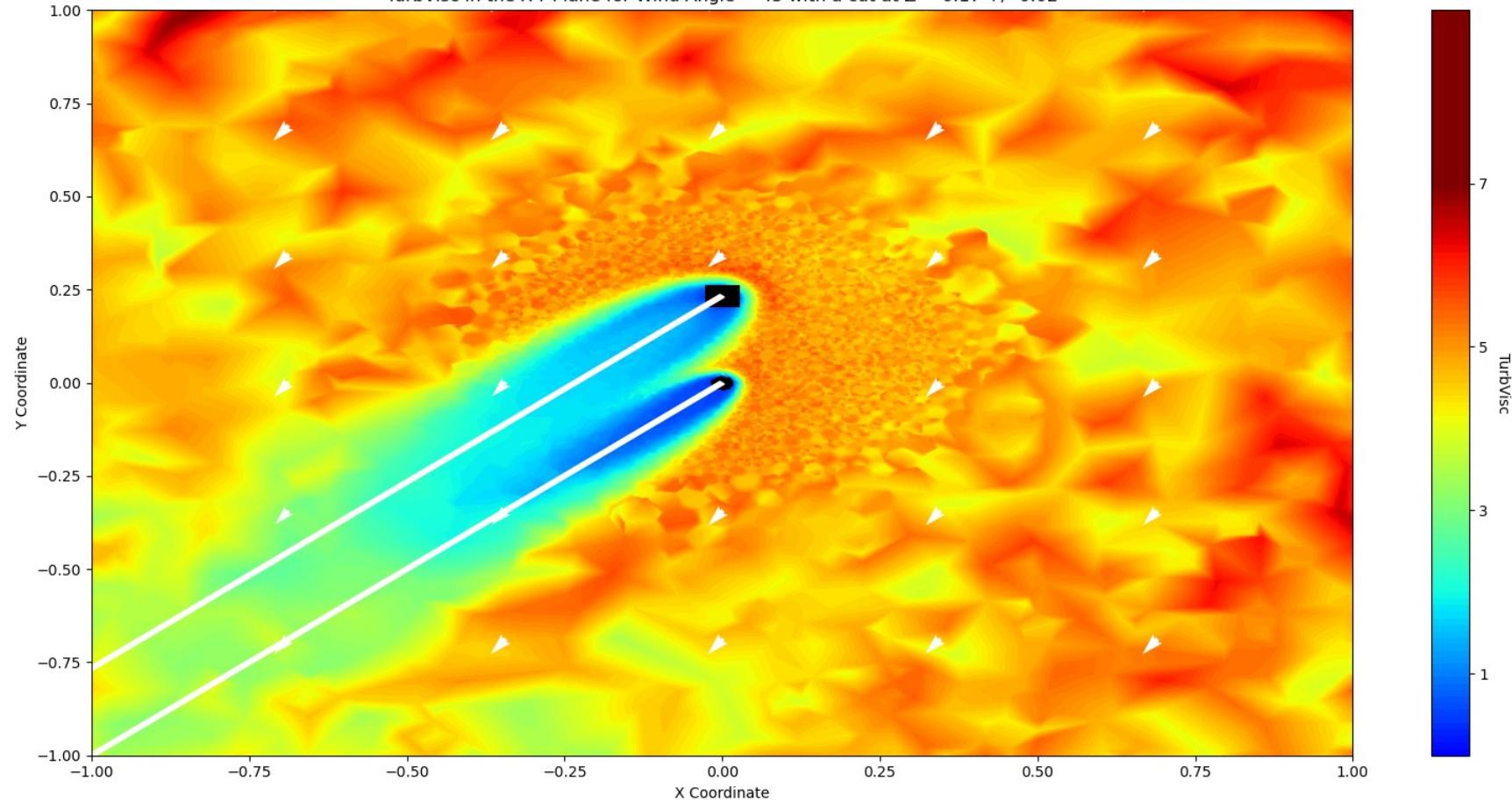
TurbVisc in the X-Y Plane for Wind Angle = 15 with a cut at Z = 0.17 +/- 0.02



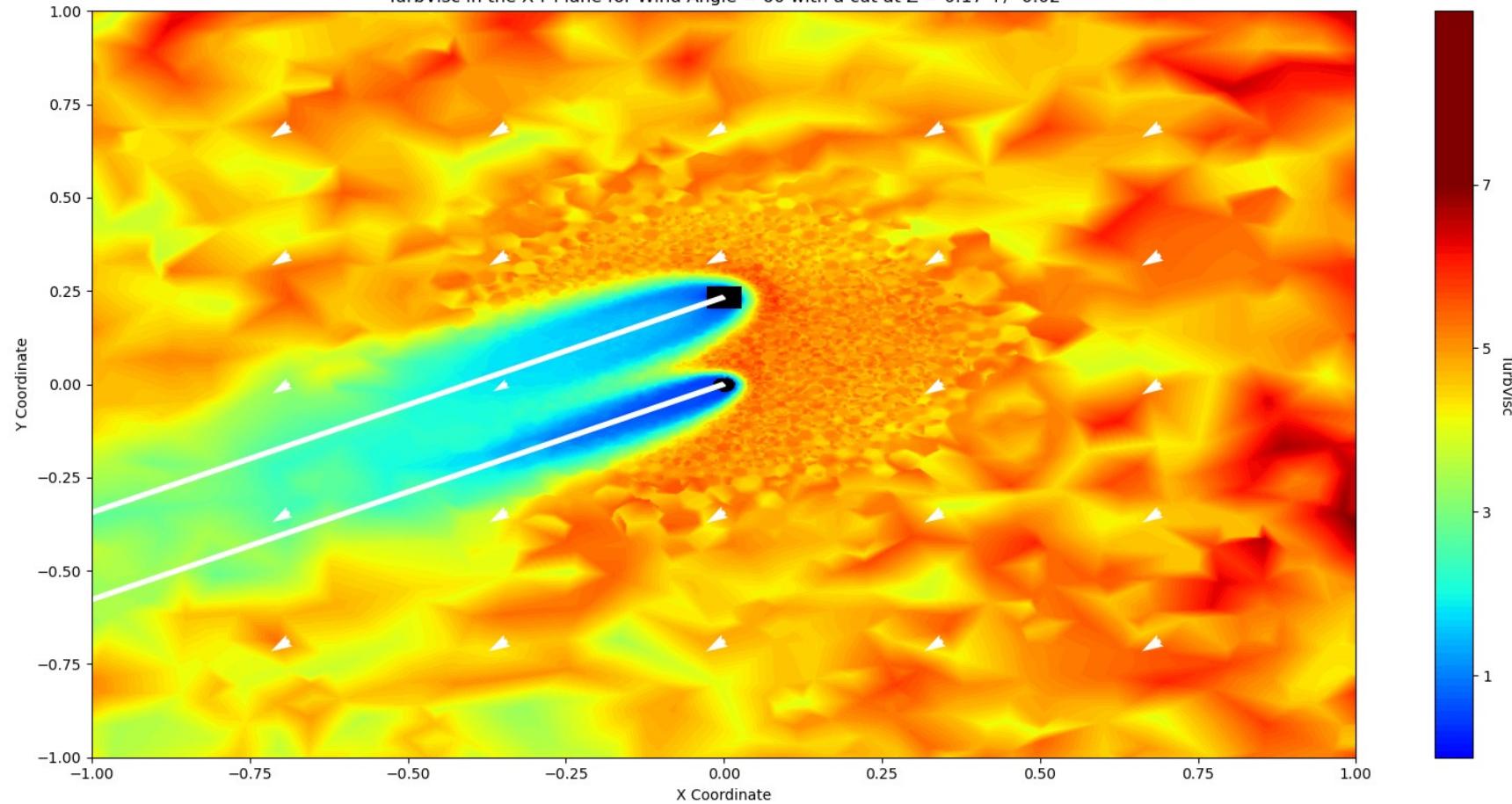
TurbVisc in the X-Y Plane for Wind Angle = 30 with a cut at Z = 0.17 +/- 0.02



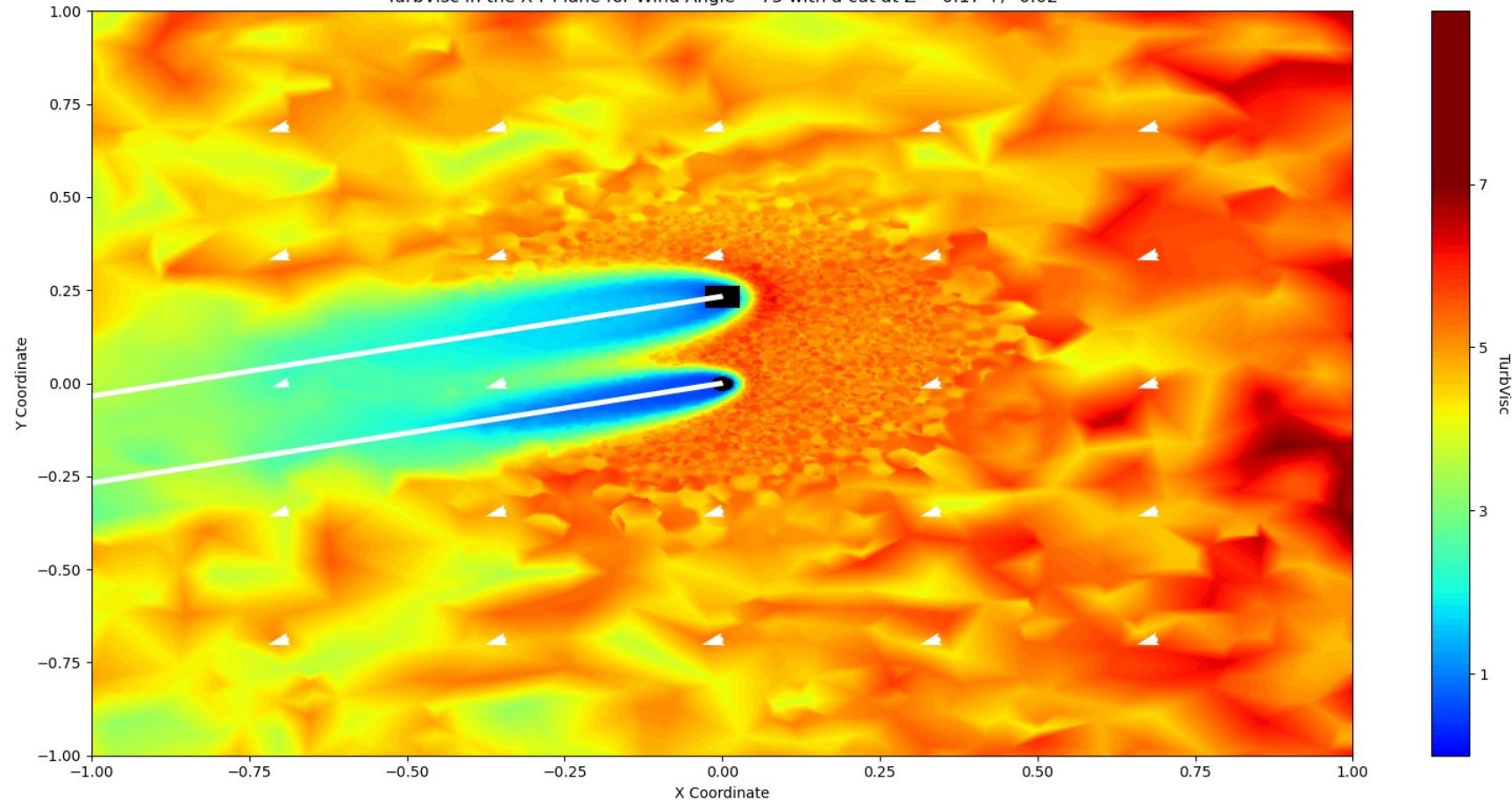
TurbVisc in the X-Y Plane for Wind Angle = 45 with a cut at Z = 0.17 +/- 0.02



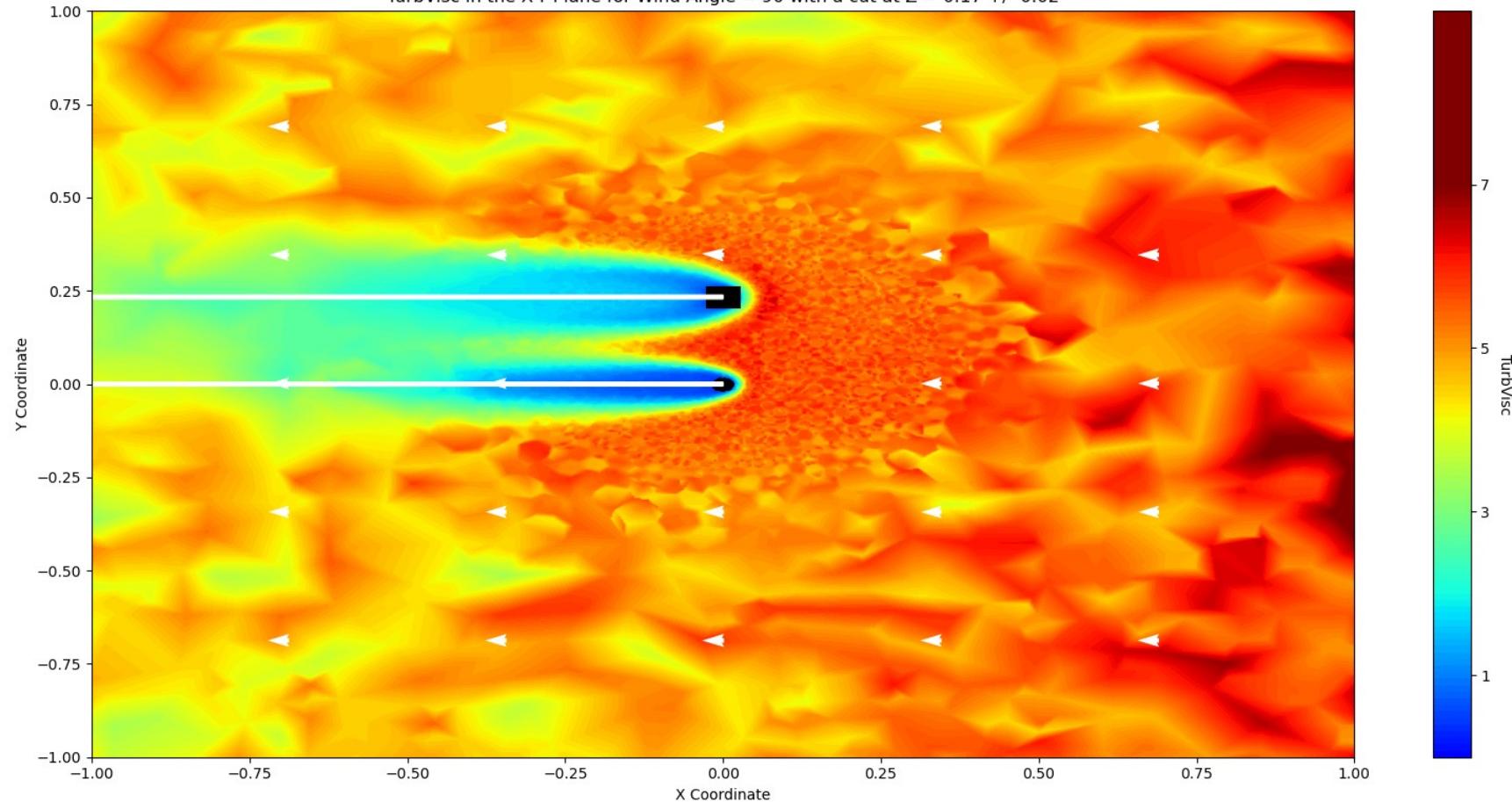
TurbVisc in the X-Y Plane for Wind Angle = 60 with a cut at Z = 0.17 +/- 0.02



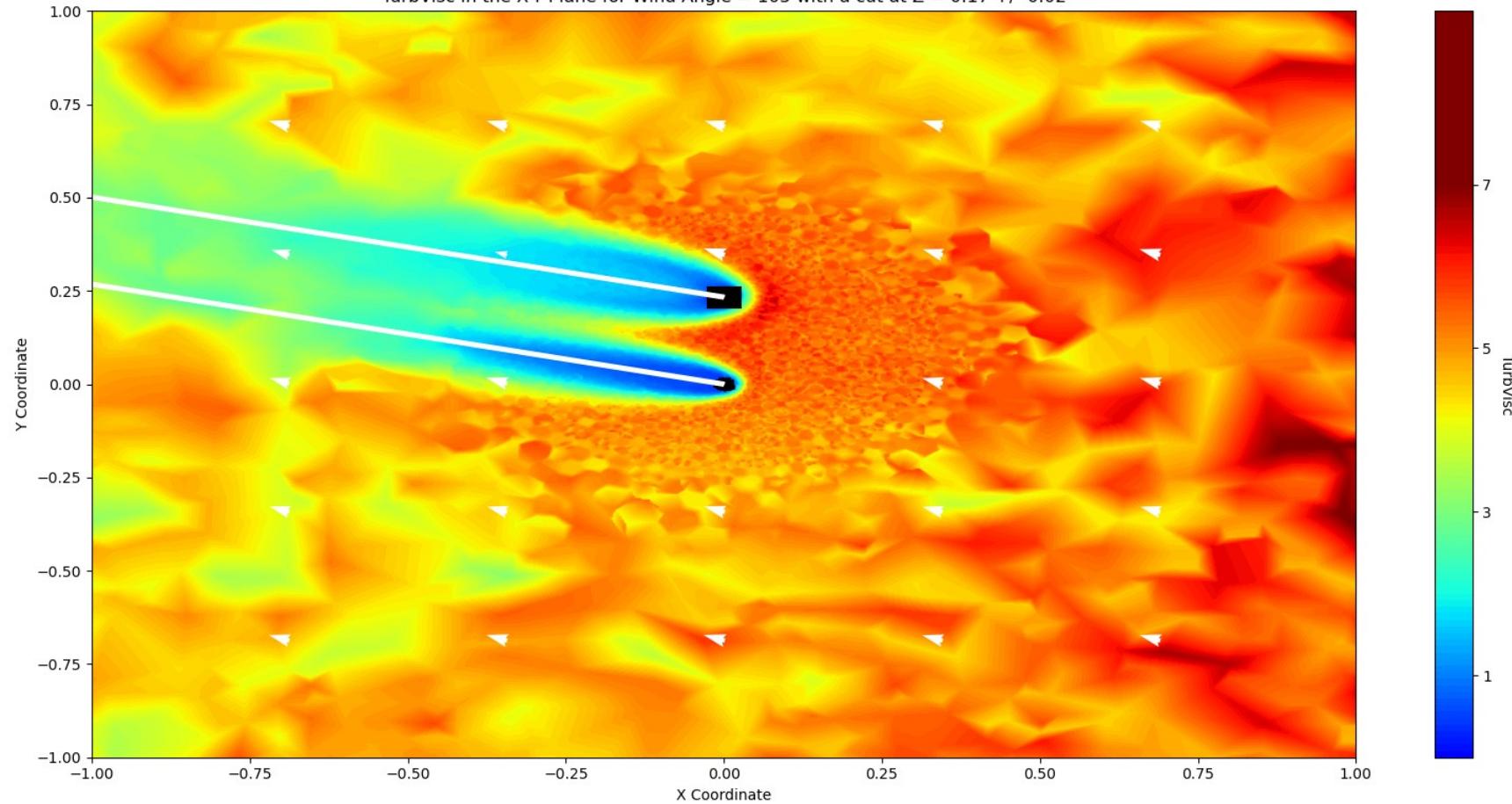
TurbVisc in the X-Y Plane for Wind Angle = 75 with a cut at Z = 0.17 +/- 0.02



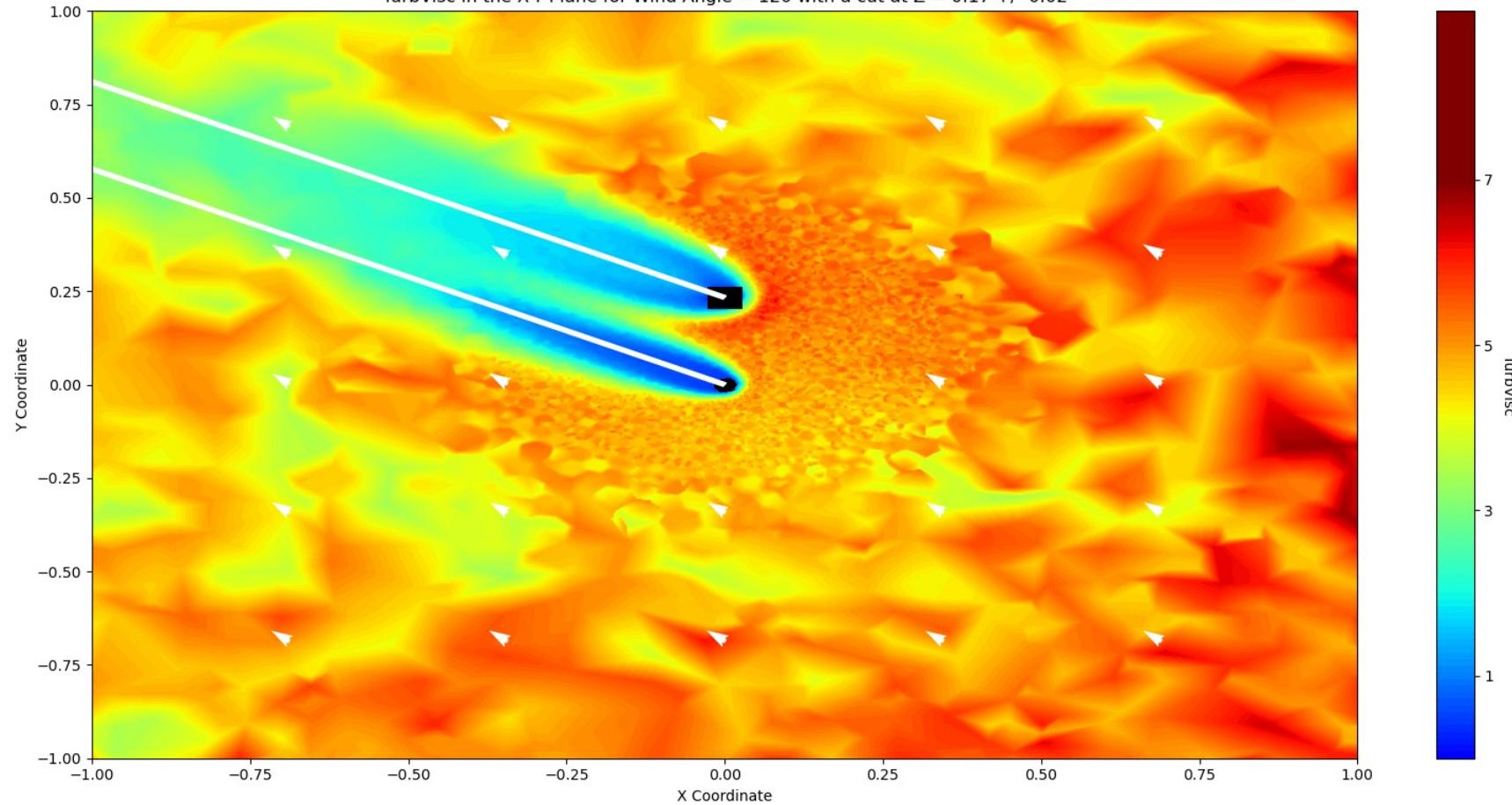
TurbVisc in the X-Y Plane for Wind Angle = 90 with a cut at Z = 0.17 +/- 0.02



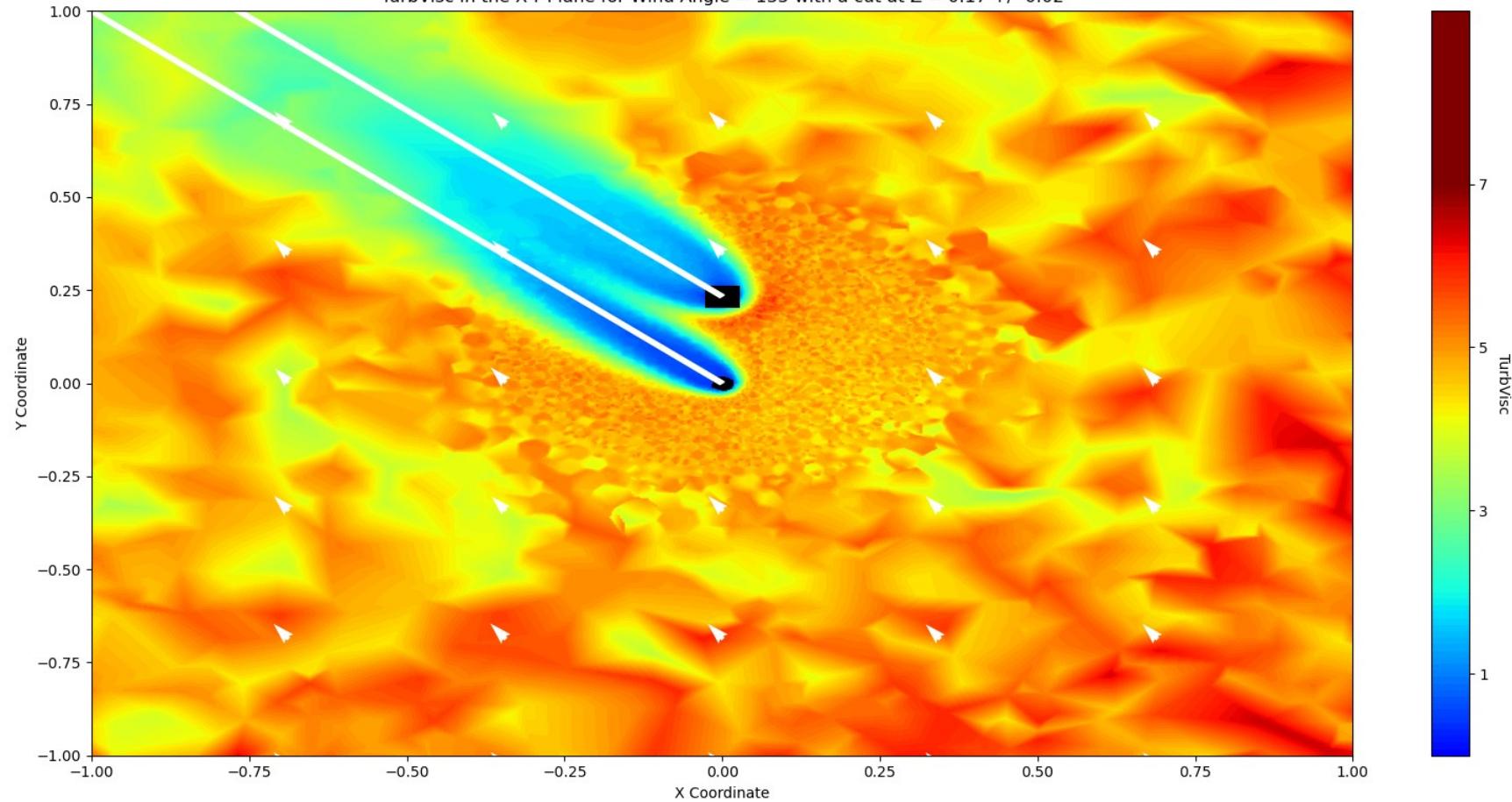
TurbVisc in the X-Y Plane for Wind Angle = 105 with a cut at Z = 0.17 +/- 0.02



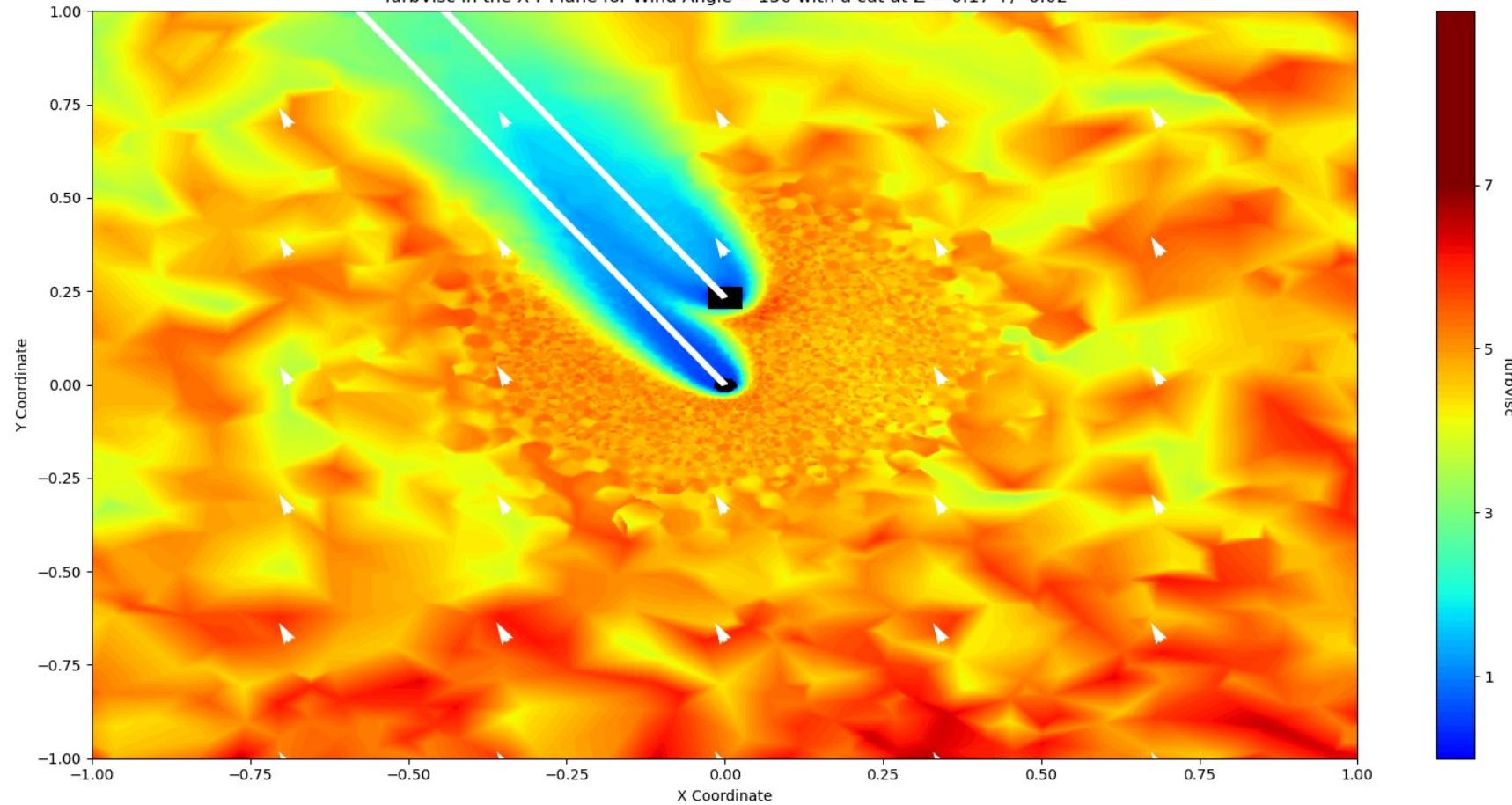
TurbVisc in the X-Y Plane for Wind Angle = 120 with a cut at Z = 0.17 +/- 0.02



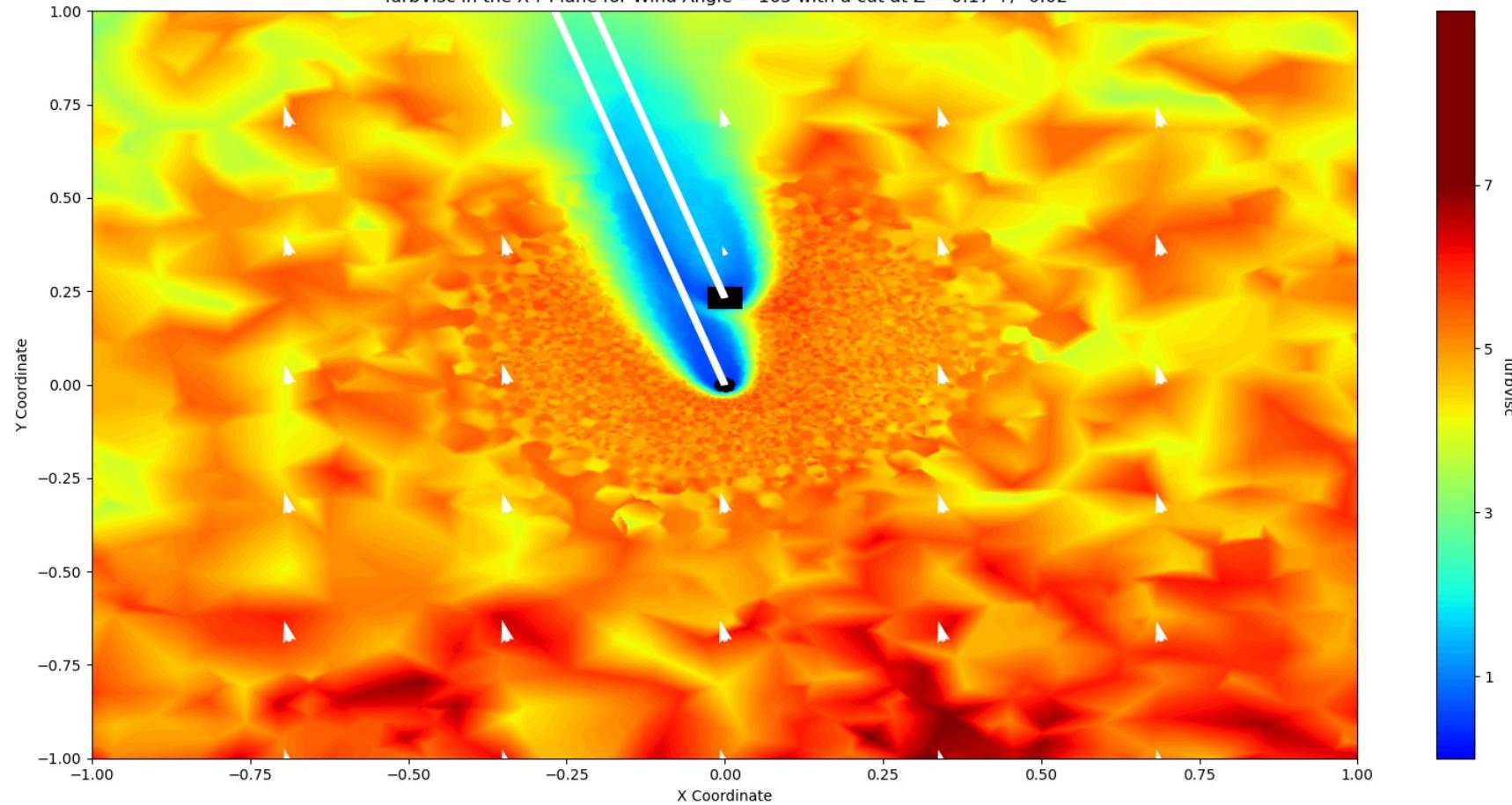
TurbVisc in the X-Y Plane for Wind Angle = 135 with a cut at Z = 0.17 +/- 0.02



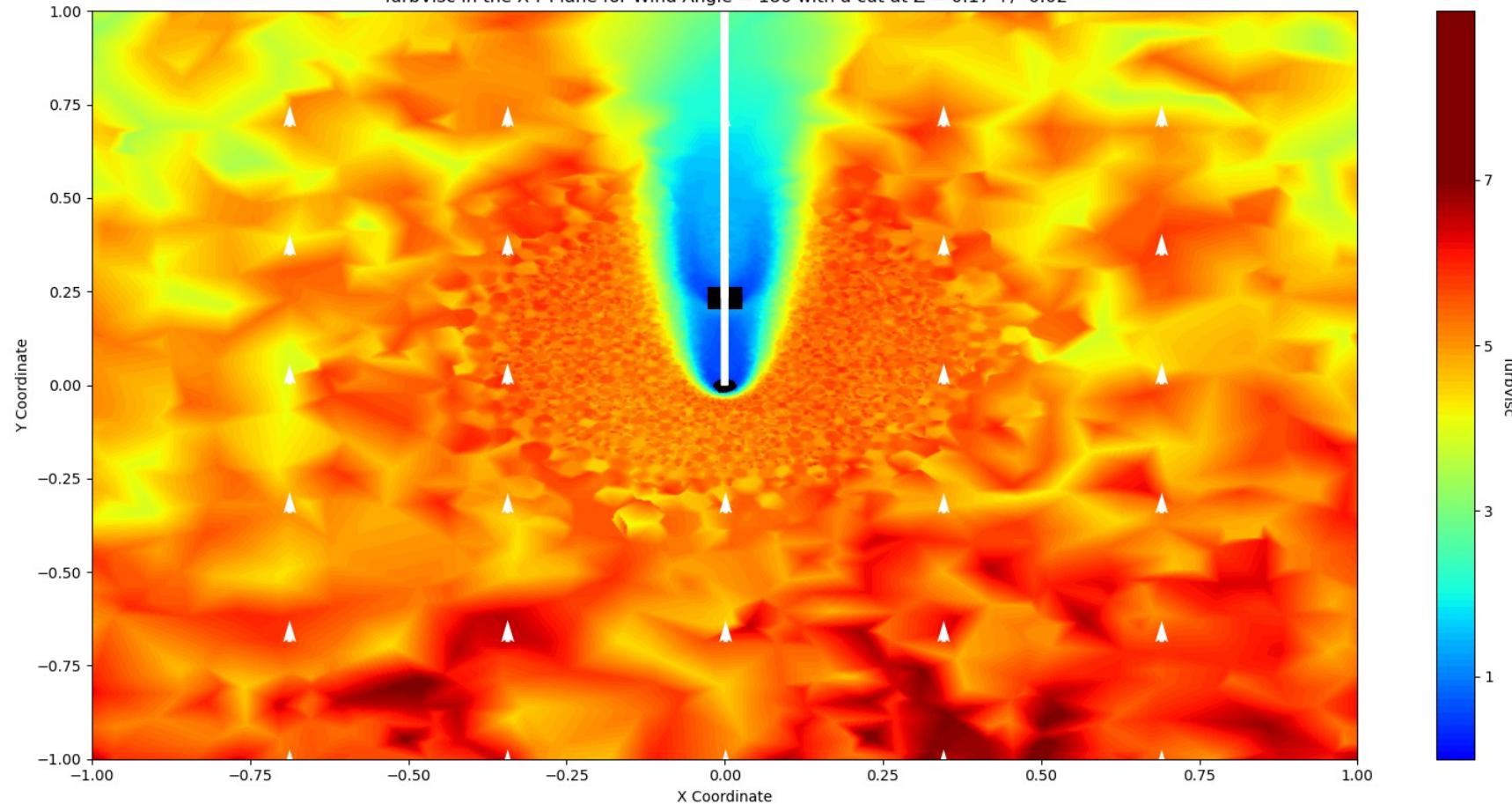
TurbVisc in the X-Y Plane for Wind Angle = 150 with a cut at Z = 0.17 +/- 0.02



TurbVisc in the X-Y Plane for Wind Angle = 165 with a cut at Z = 0.17 +/- 0.02



TurbVisc in the X-Y Plane for Wind Angle = 180 with a cut at Z = 0.17 +/- 0.02



Scripts v4 – Preliminary Results

Some Parameters

Infinite epochs - instead the criteria for stopping is $\text{loss}_{\{n\}} - \text{loss}_{\{n-1\}} < \epsilon$ for 10 consecutive epochs where n is the epoch number and $\epsilon = 1E-5$ (user defined)

128 Neurons for the PINN unless otherwise specified

We have the data for 13 angles, [0, 15, 30, 45, 60, 75, 90, 105, 120, 135, 150, 165, 180] in degrees

We concatenate the data for angles = [0, 15, 30, 45, 60, 75, 90, 105, 120, 130, 150, 165, 180] and then take 99% of the dataset with random seed = 42 for training and 1% for testing

By using 99% of the whole dataset we hope to make the NN learn about wind angle such that the parameters become functions of the wind angle

Then using the trained neural network we predict the data for angle = 135

For this run, we will only have input parameters to be [X, Y, Z, $\cos(\theta)$, $\sin(\theta)$] and the output parameters will be [U, V, W]

Progress so far - Data Loss Only
Standard Normal Scalar
(Adam Optimizer)

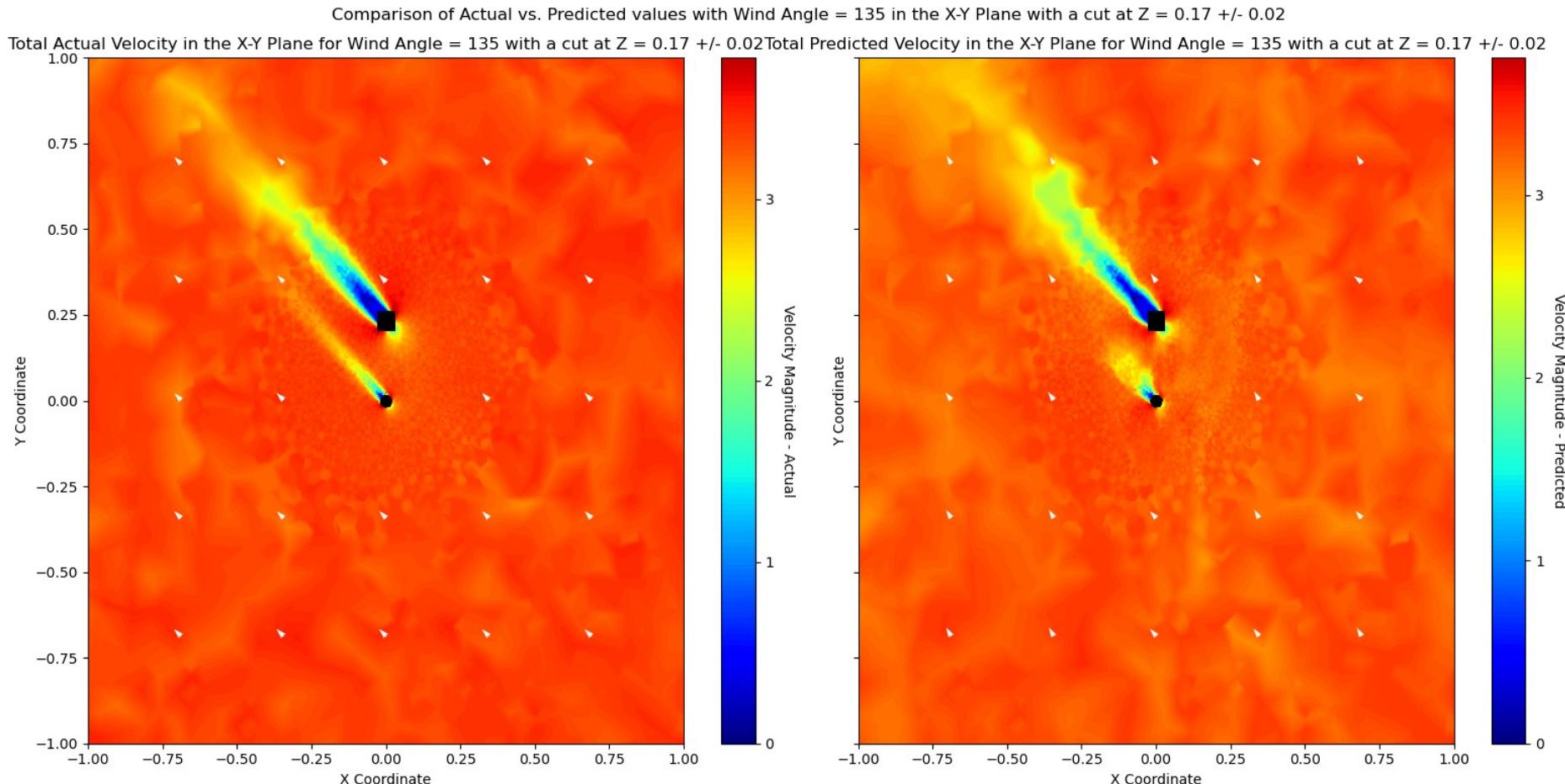
Threshold = 1E-5 (4900 Epochs, not completed), GPU Laptop

Scripts v4 – PREDICTING (135 DEG)

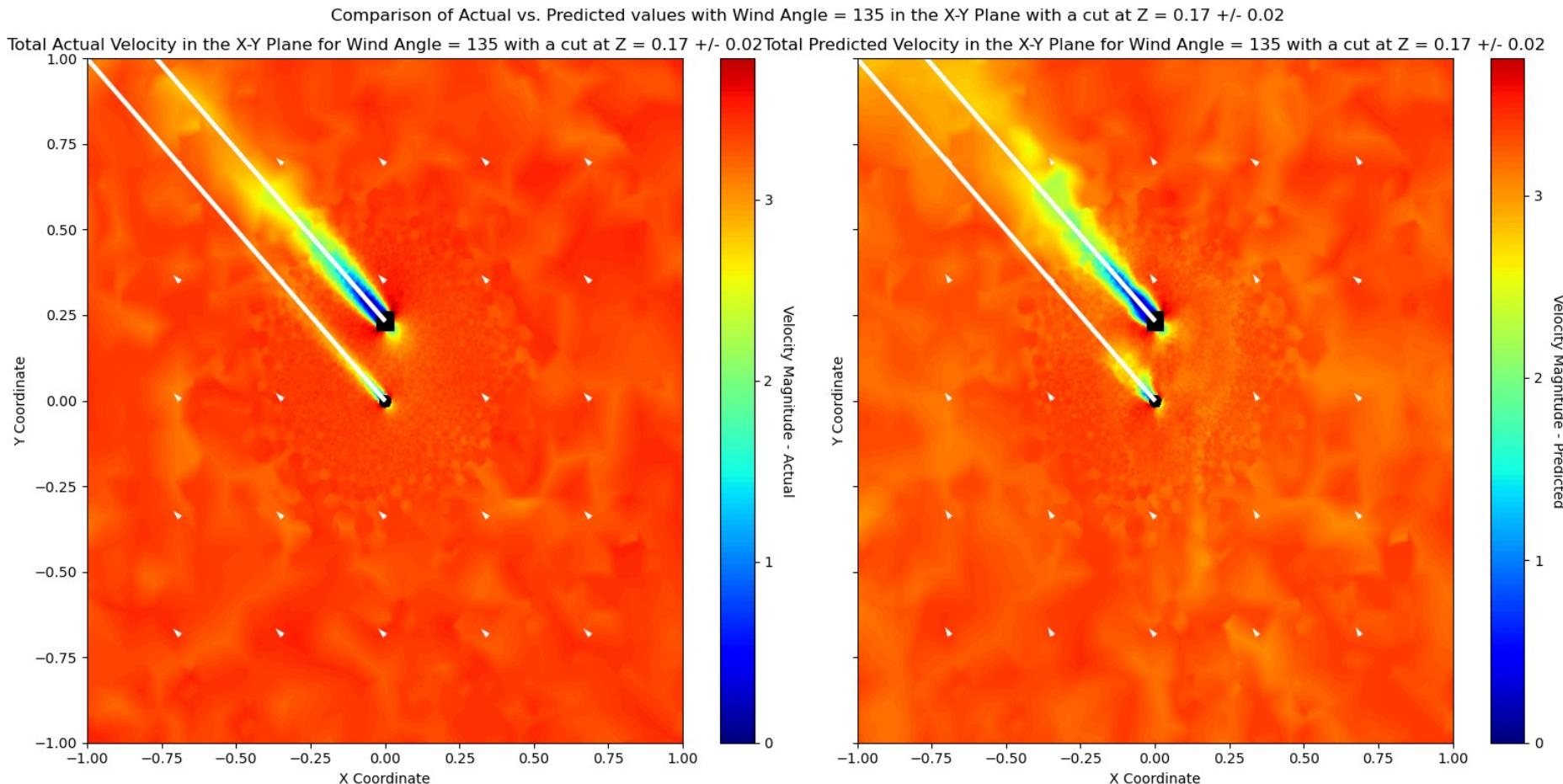
Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar)
Threshold = 1E-5 (4900 Epochs, so far...), GPU Laptop
Predicting Results – Metrics (Angle = 135)

Variable	MSE	RMSE	MAE	R2
Velocity:0	0.308634757506756	0.55554905949588	0.464360776797406	0.697187485161744
Velocity:1	0.270307209787731	0.519910770986455	0.433073047598817	0.737320425082821
Velocity:2	0.00128996226831055	0.0359160447197426	0.0130729691069715	0.960568566914327

Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar), Threshold = 1E-5 (4900 Epochs, so far...), GPU Laptop
Predicting Results - X-Y Total Velocity Plot (Angle = 135)



Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar), Threshold = 1E-5 (4900 Epochs, so far...), GPU Laptop
Predicting Results - X-Y Total Velocity Plot (Angle = 135)

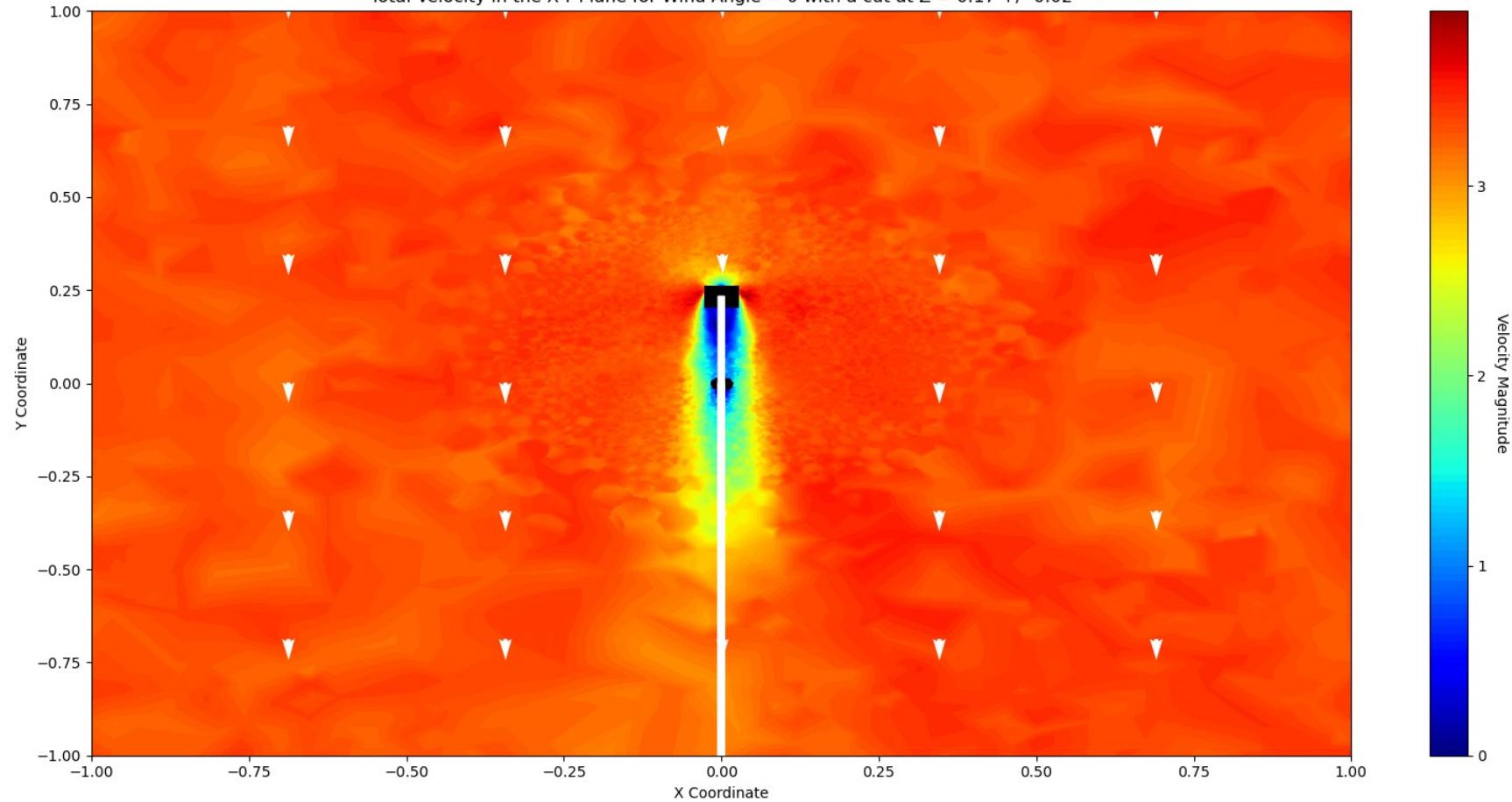


Progress so far - Data Loss Only
Standard Normal Scalar
(Adam Optimizer)

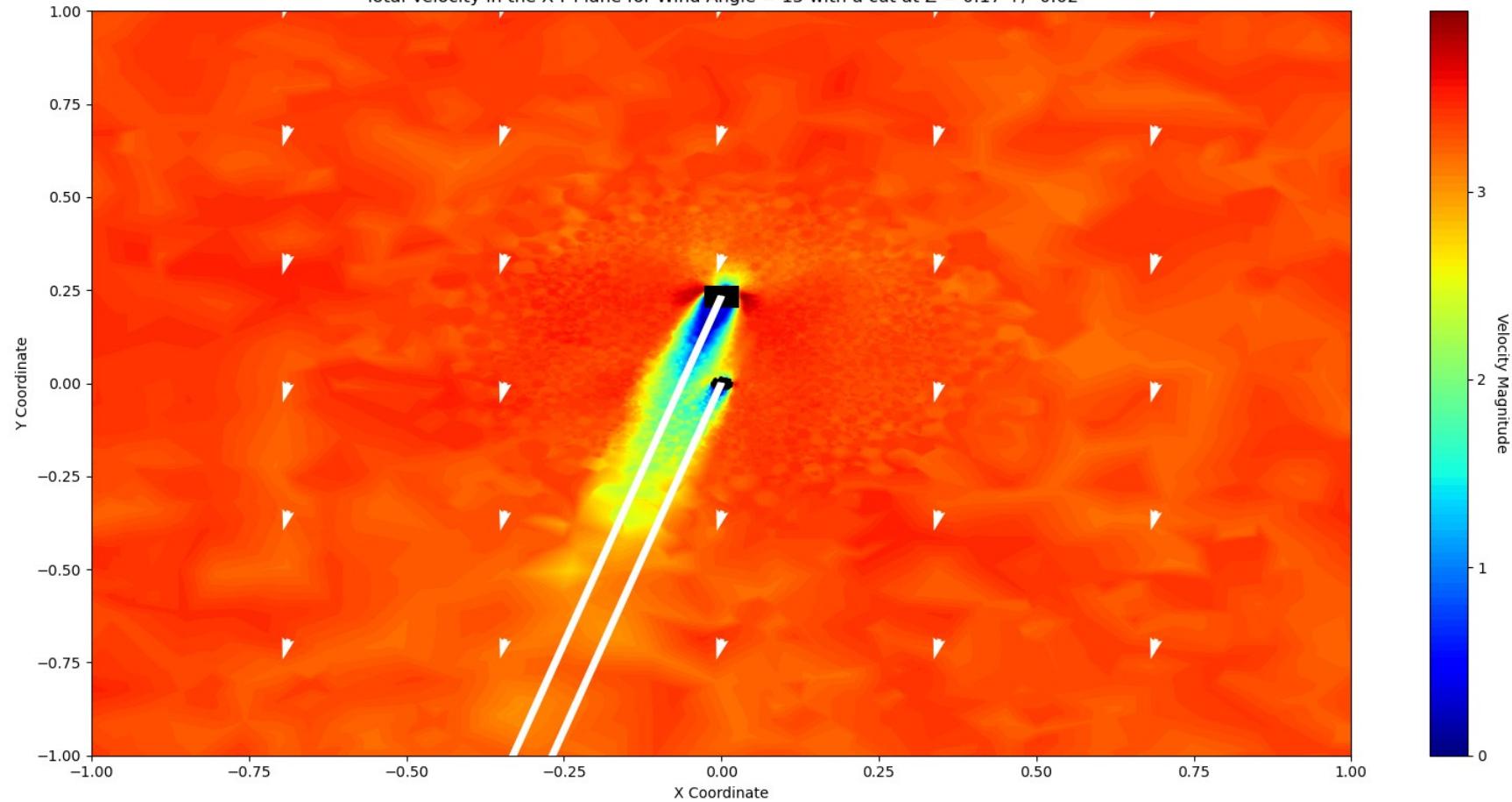
Threshold = 1E-5 (4900 Epochs, not completed), GPU Laptop

Scripts v4 – Plotting Any Angle

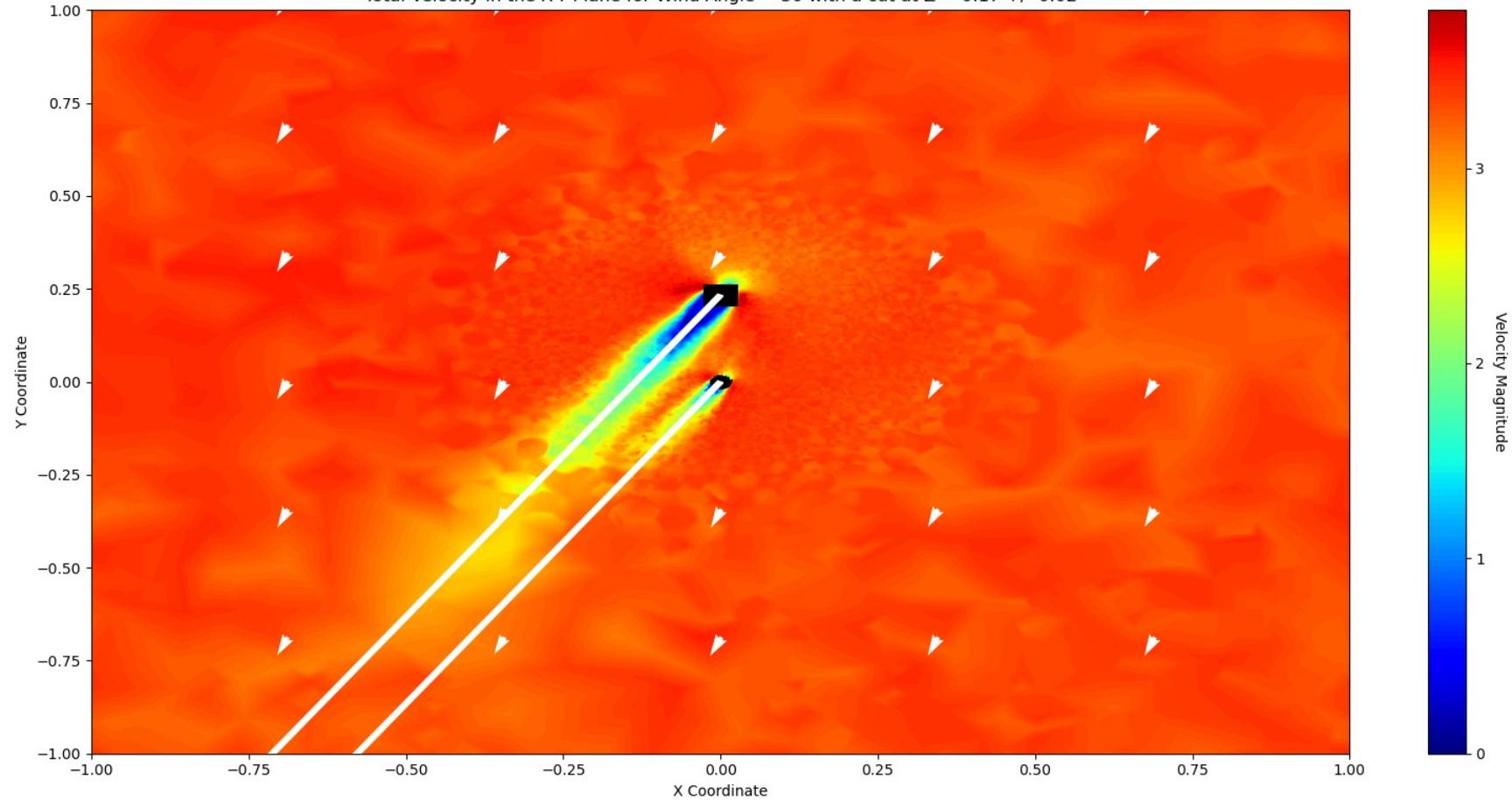
Total Velocity in the X-Y Plane for Wind Angle = 0 with a cut at Z = 0.17 +/- 0.02



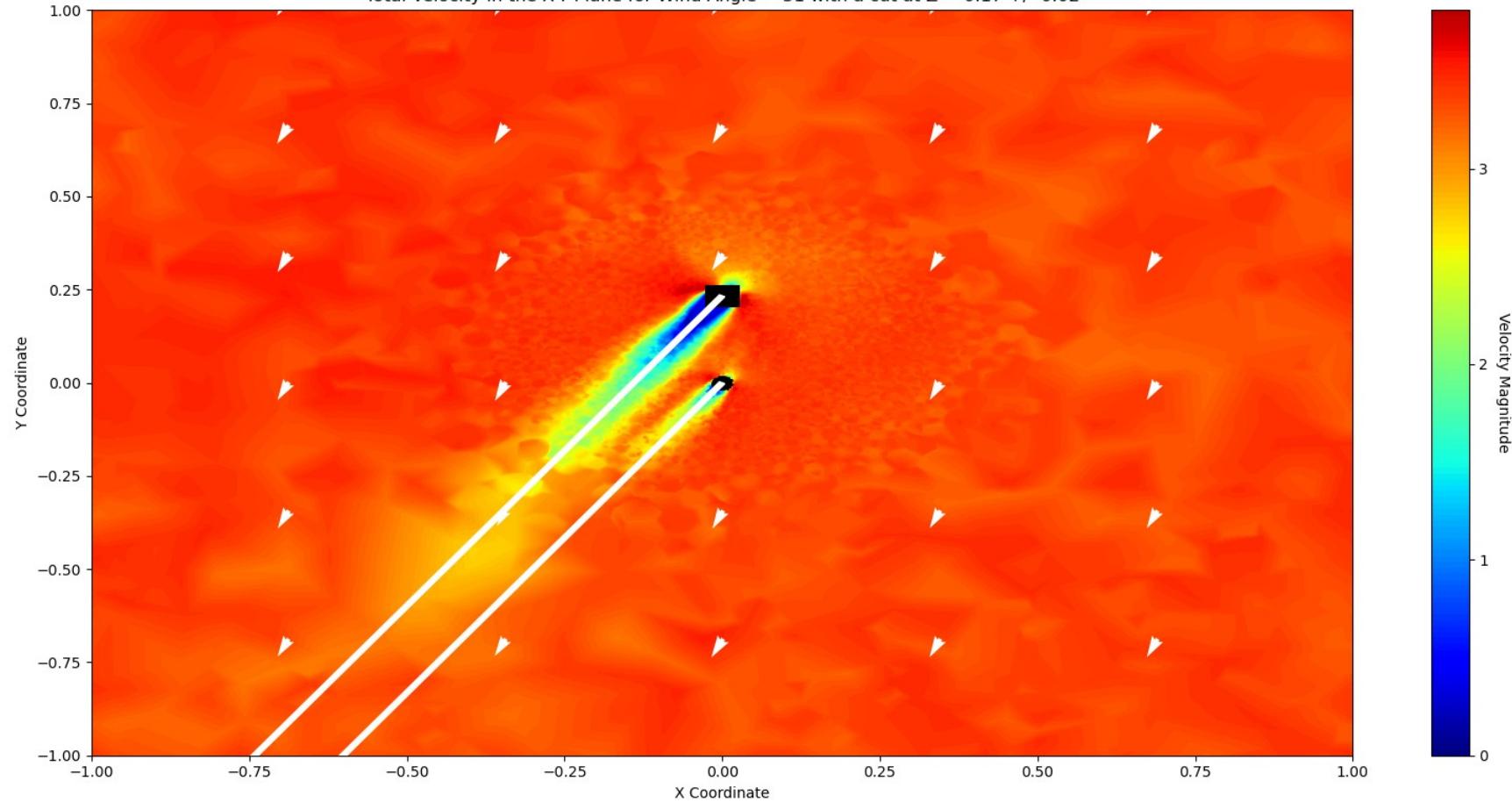
Total Velocity in the X-Y Plane for Wind Angle = 15 with a cut at Z = 0.17 +/- 0.02



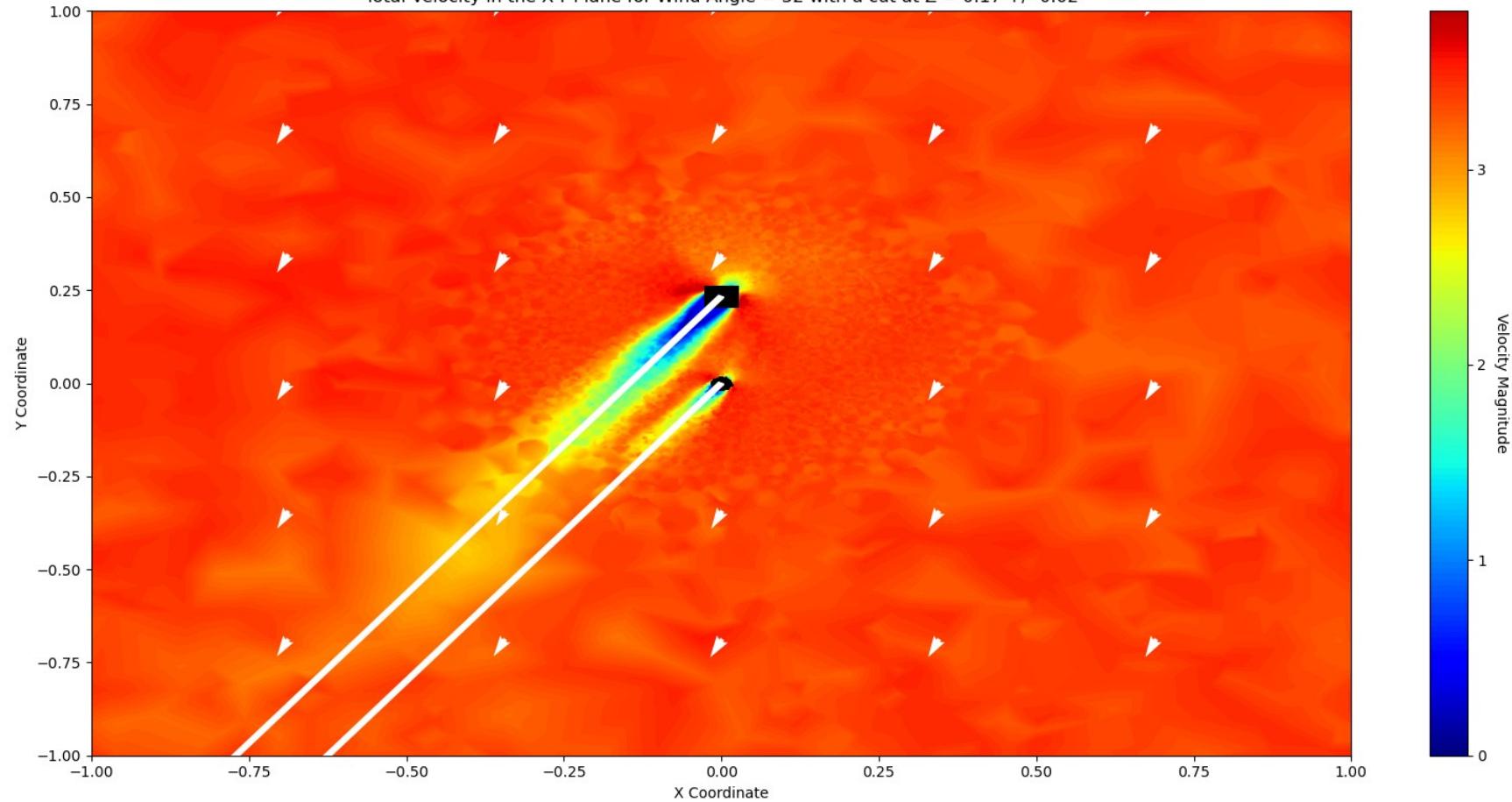
Total Velocity in the X-Y Plane for Wind Angle = 30 with a cut at Z = 0.17 +/- 0.02



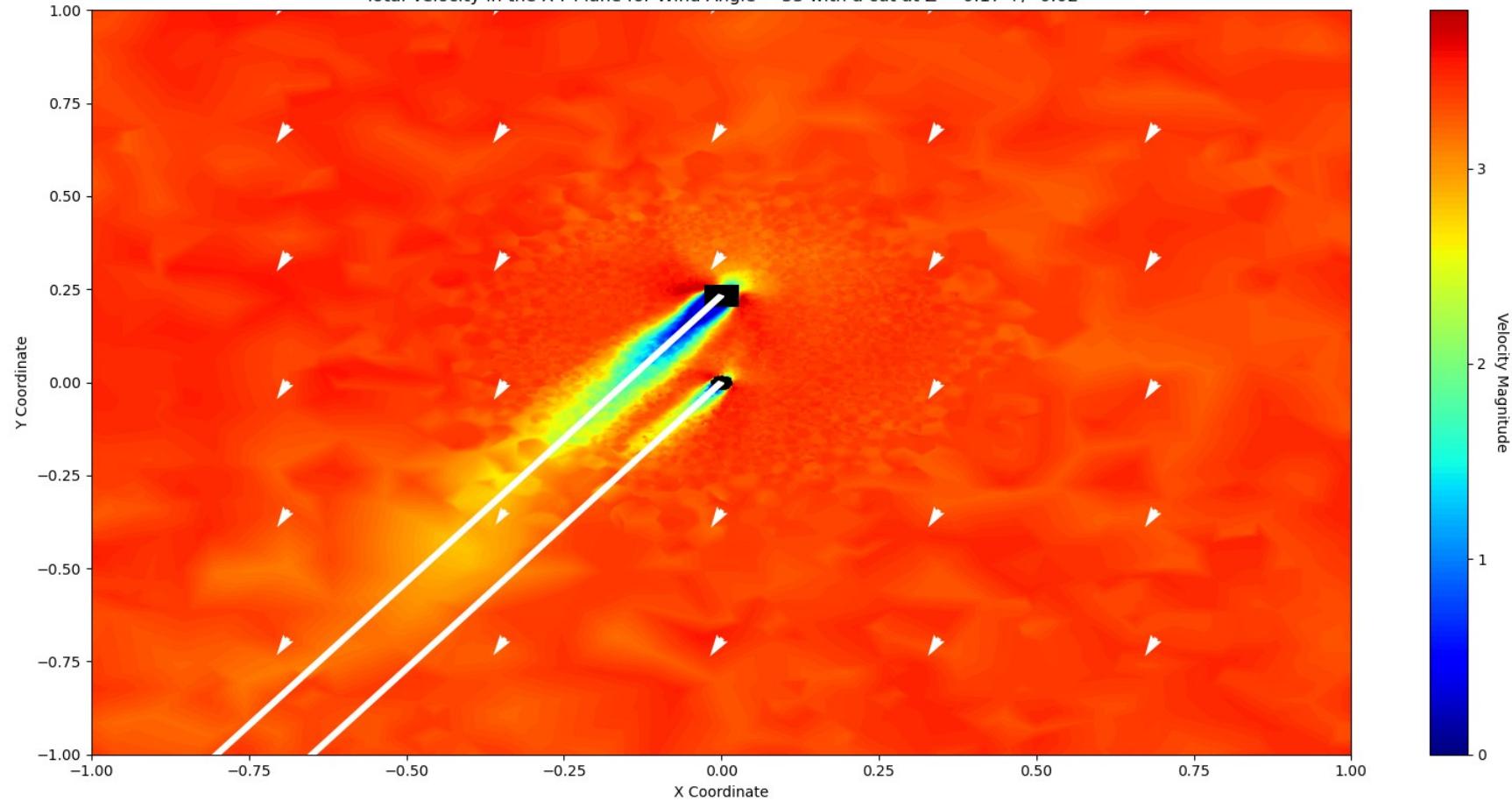
Total Velocity in the X-Y Plane for Wind Angle = 31 with a cut at Z = 0.17 +/- 0.02



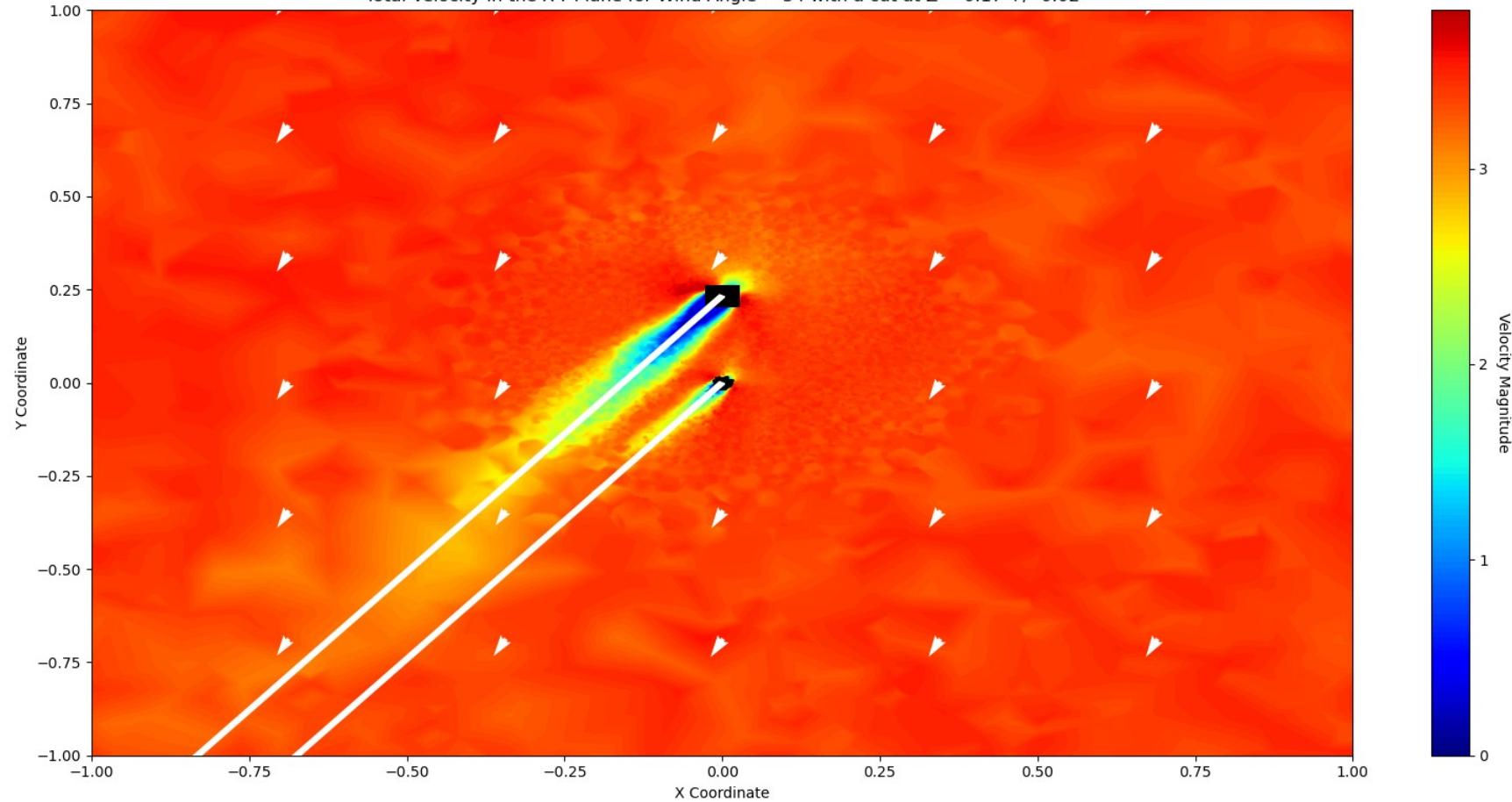
Total Velocity in the X-Y Plane for Wind Angle = 32 with a cut at Z = 0.17 +/- 0.02



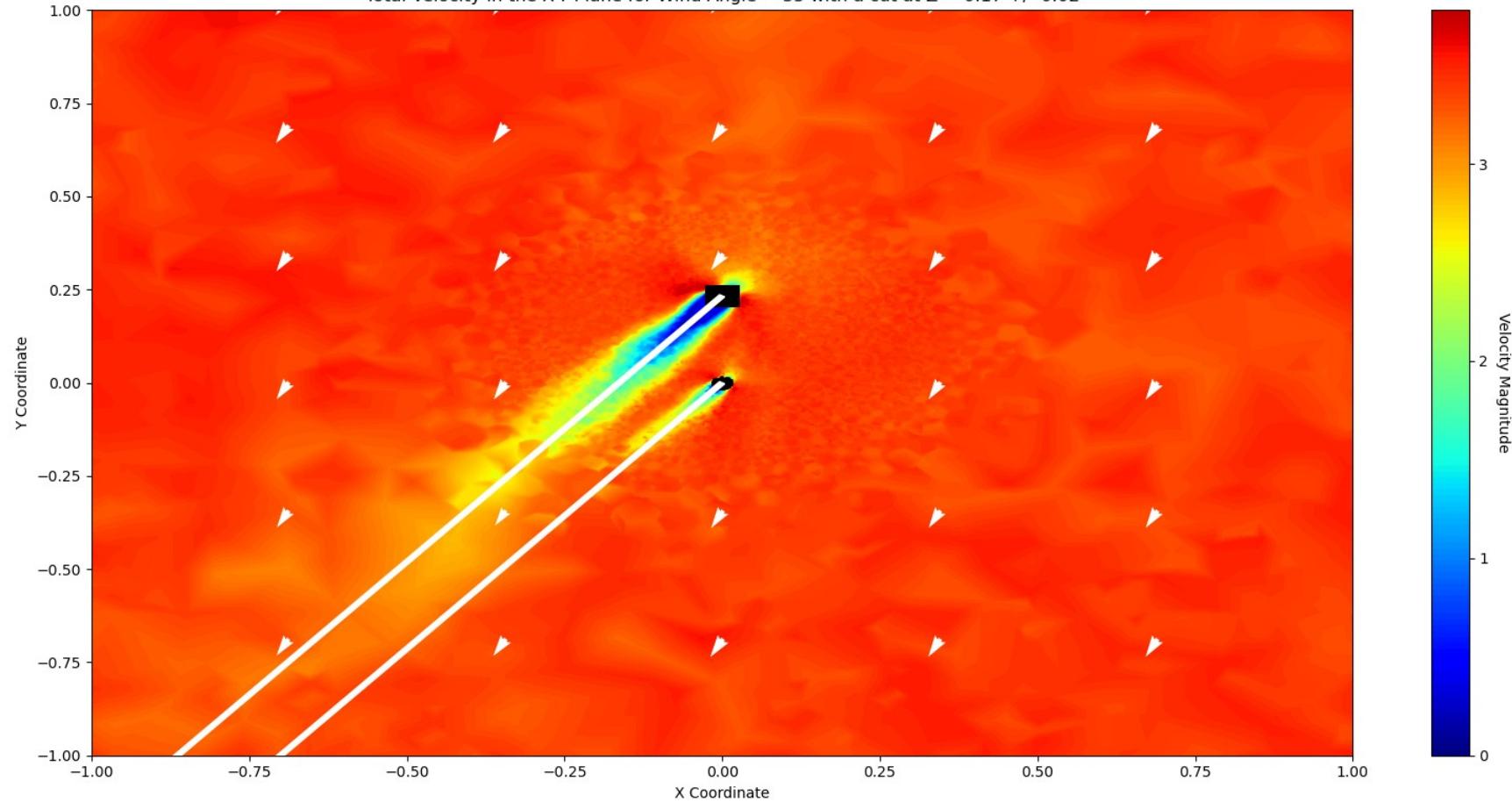
Total Velocity in the X-Y Plane for Wind Angle = 33 with a cut at Z = 0.17 +/- 0.02



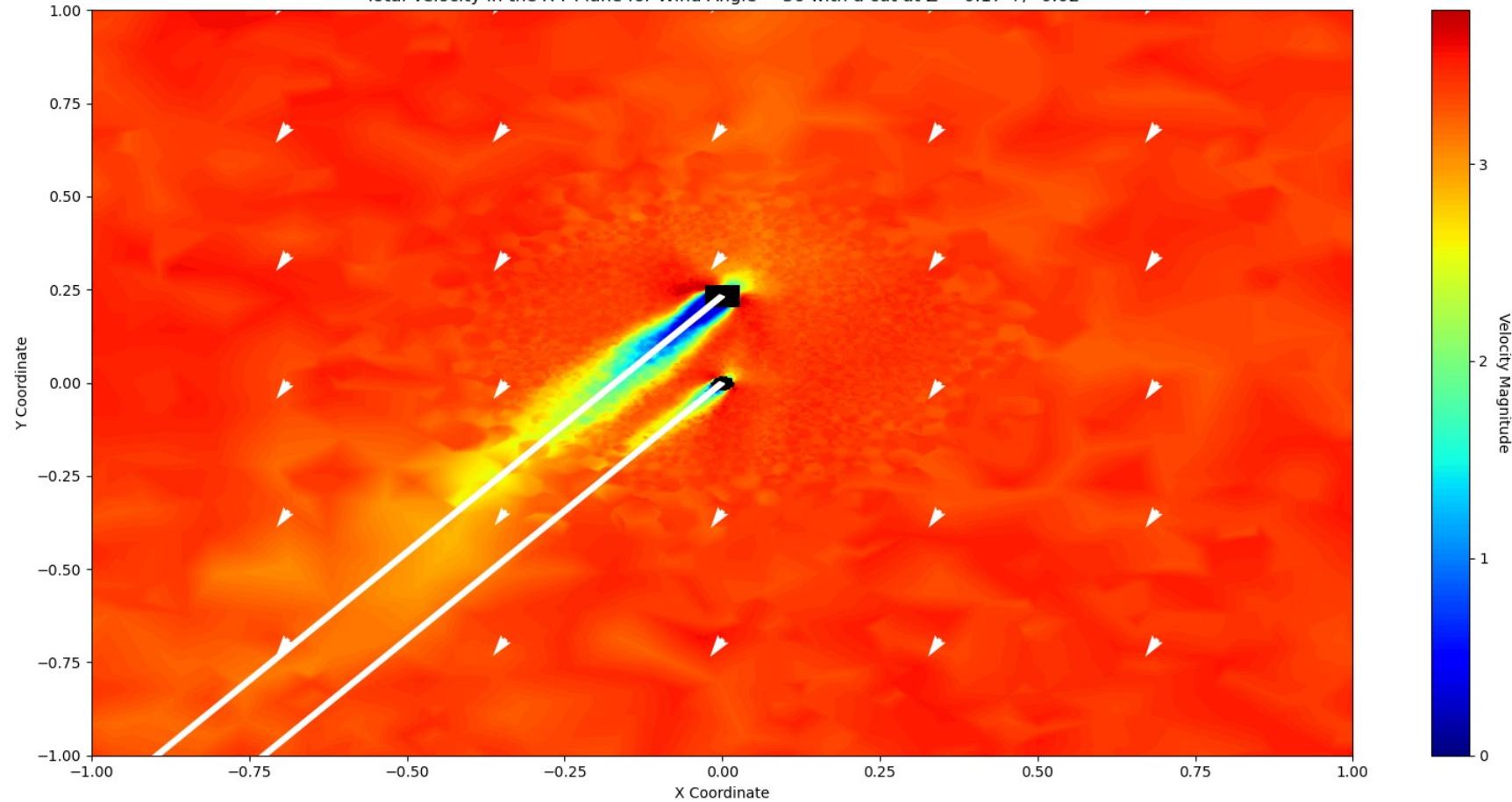
Total Velocity in the X-Y Plane for Wind Angle = 34 with a cut at Z = 0.17 +/- 0.02



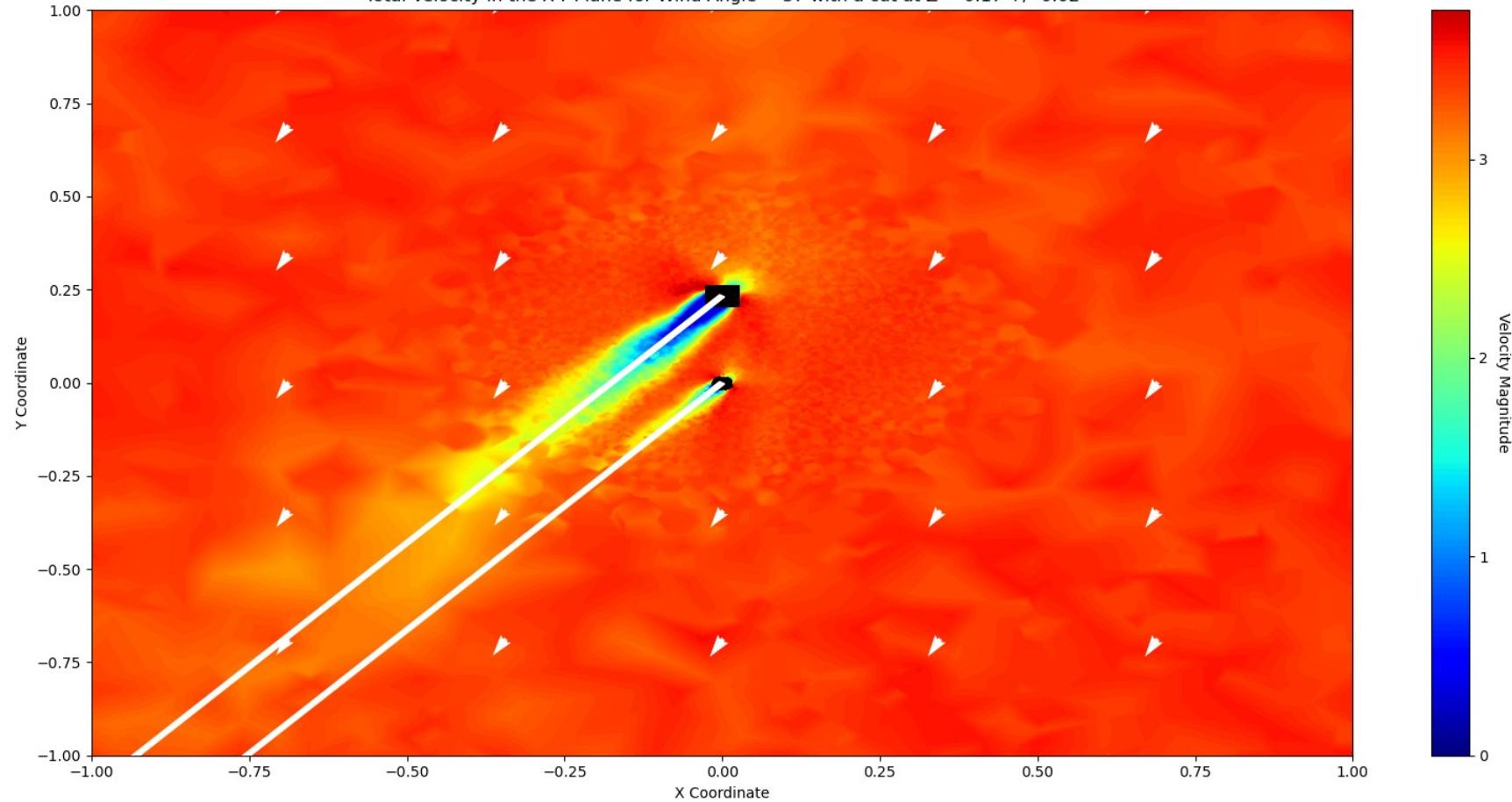
Total Velocity in the X-Y Plane for Wind Angle = 35 with a cut at Z = 0.17 +/- 0.02



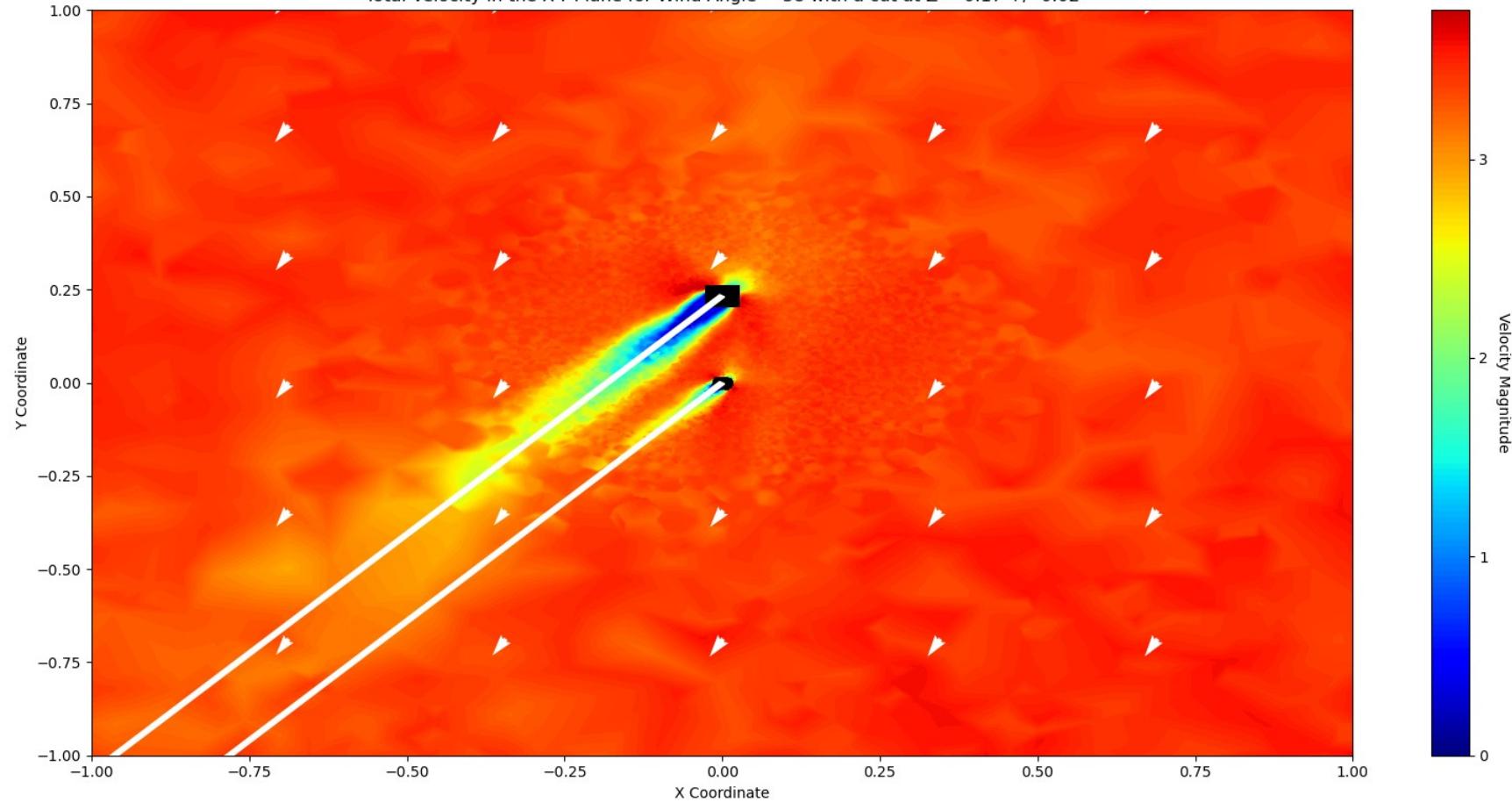
Total Velocity in the X-Y Plane for Wind Angle = 36 with a cut at Z = 0.17 +/- 0.02



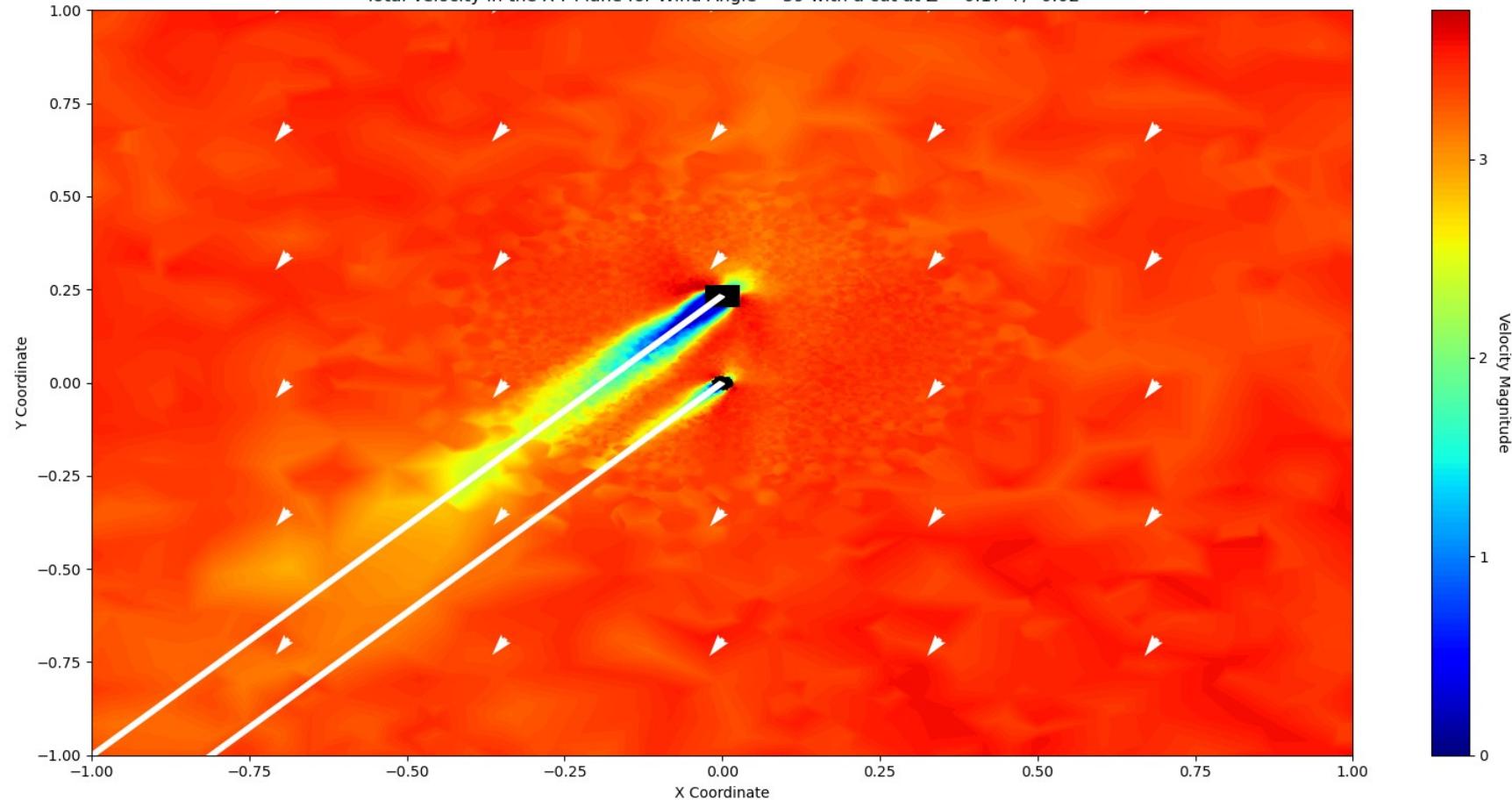
Total Velocity in the X-Y Plane for Wind Angle = 37 with a cut at Z = 0.17 +/- 0.02



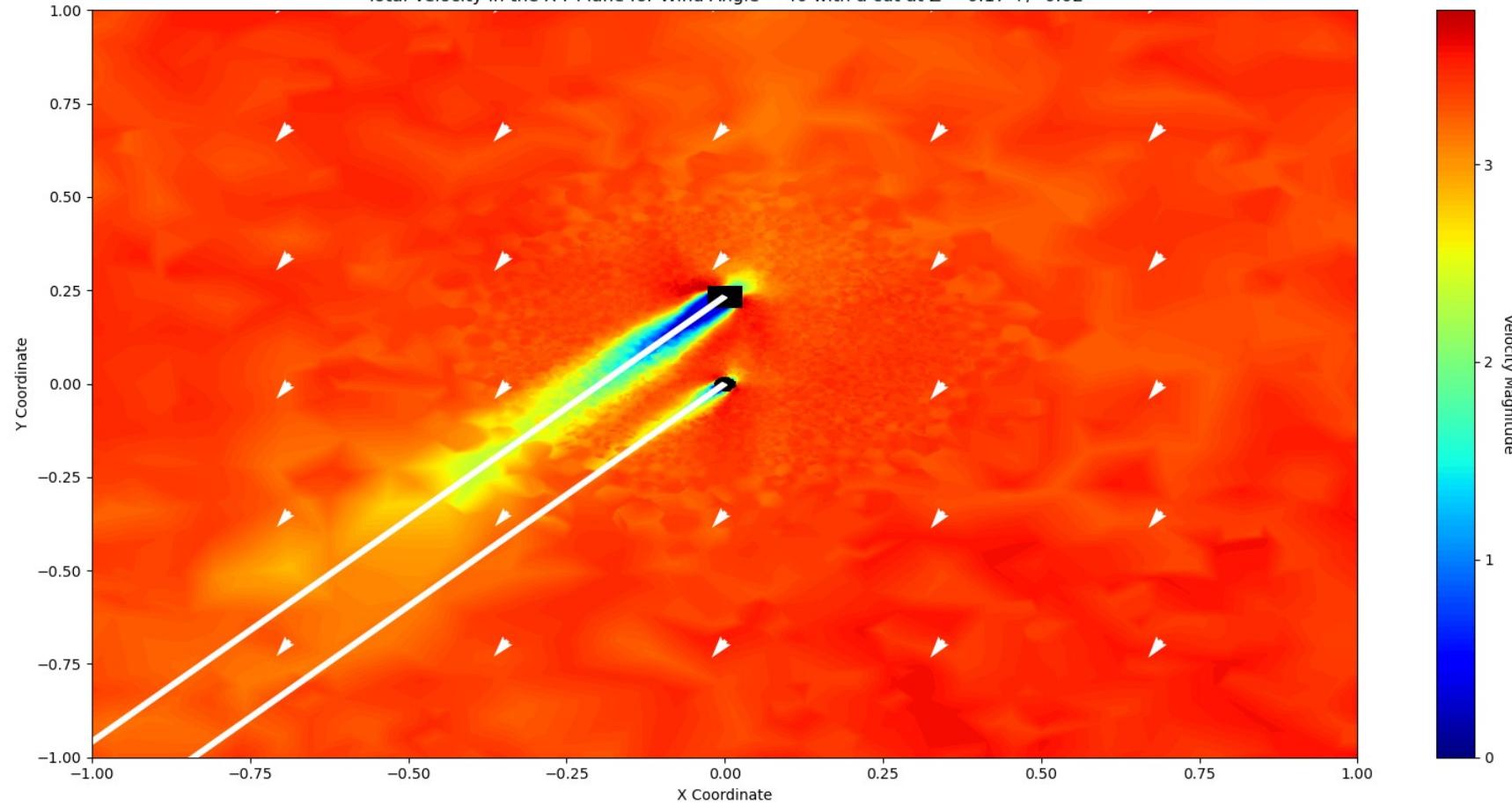
Total Velocity in the X-Y Plane for Wind Angle = 38 with a cut at Z = 0.17 +/- 0.02



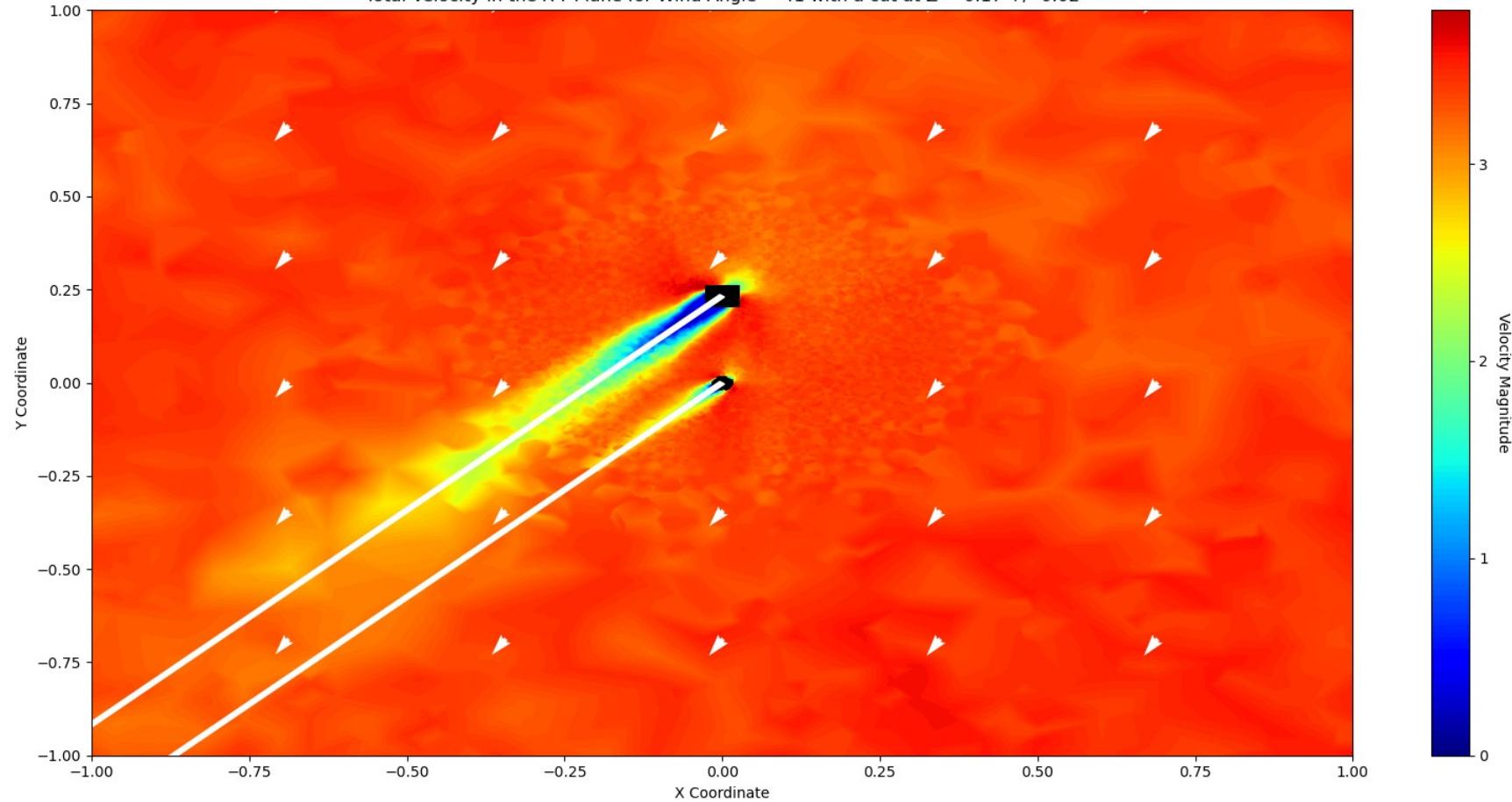
Total Velocity in the X-Y Plane for Wind Angle = 39 with a cut at Z = 0.17 +/- 0.02



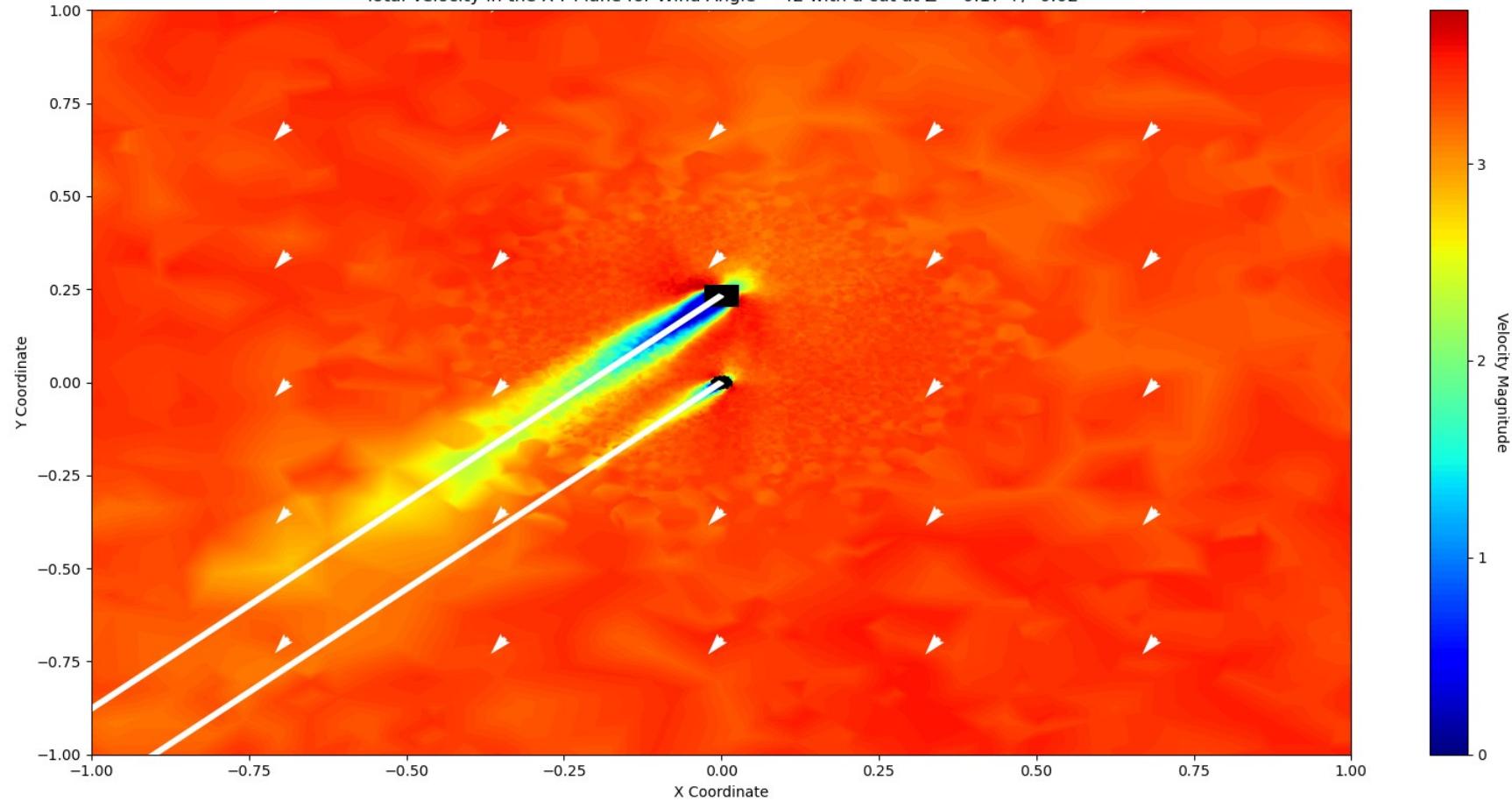
Total Velocity in the X-Y Plane for Wind Angle = 40 with a cut at Z = 0.17 +/- 0.02



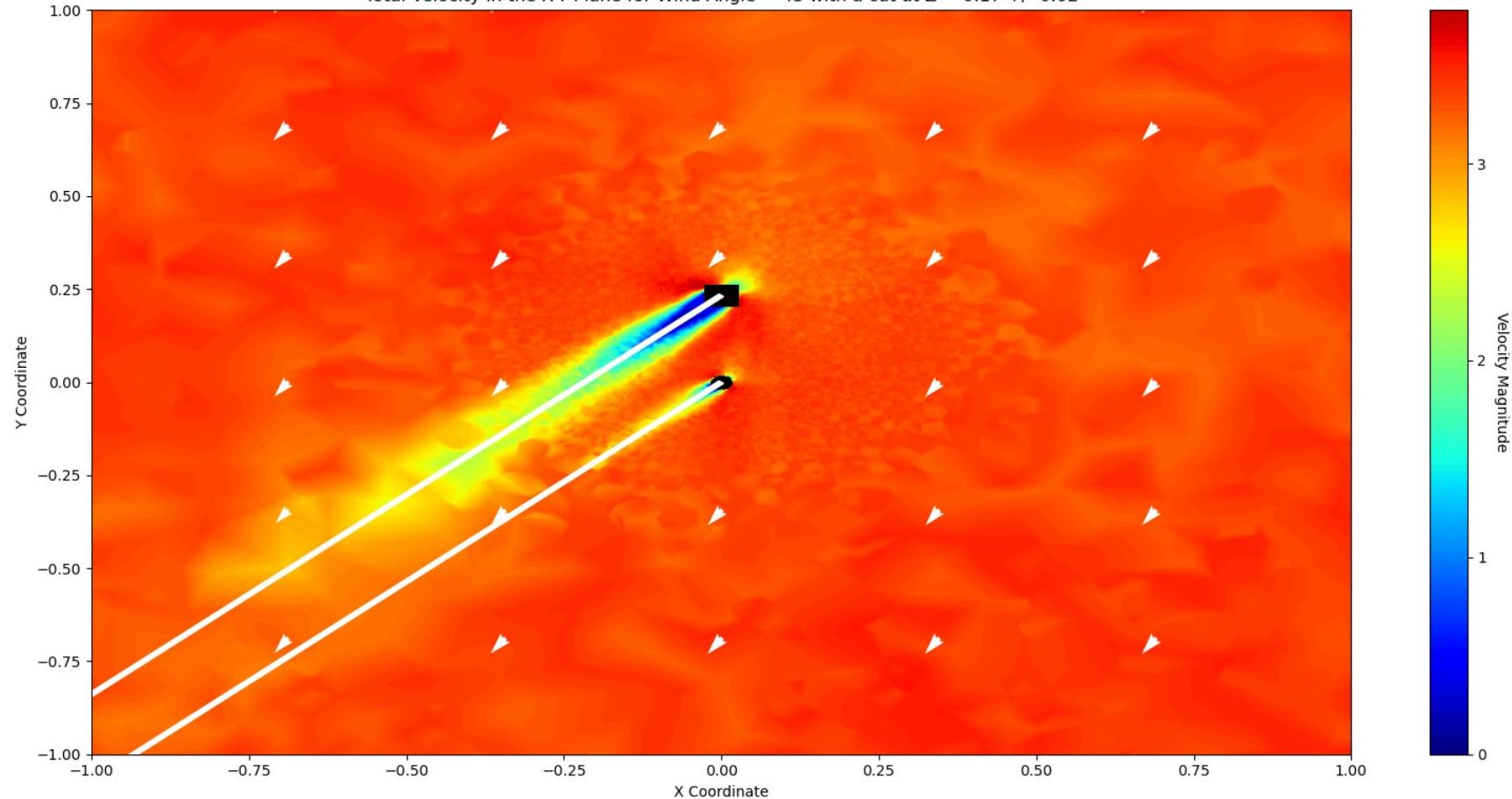
Total Velocity in the X-Y Plane for Wind Angle = 41 with a cut at Z = 0.17 +/- 0.02



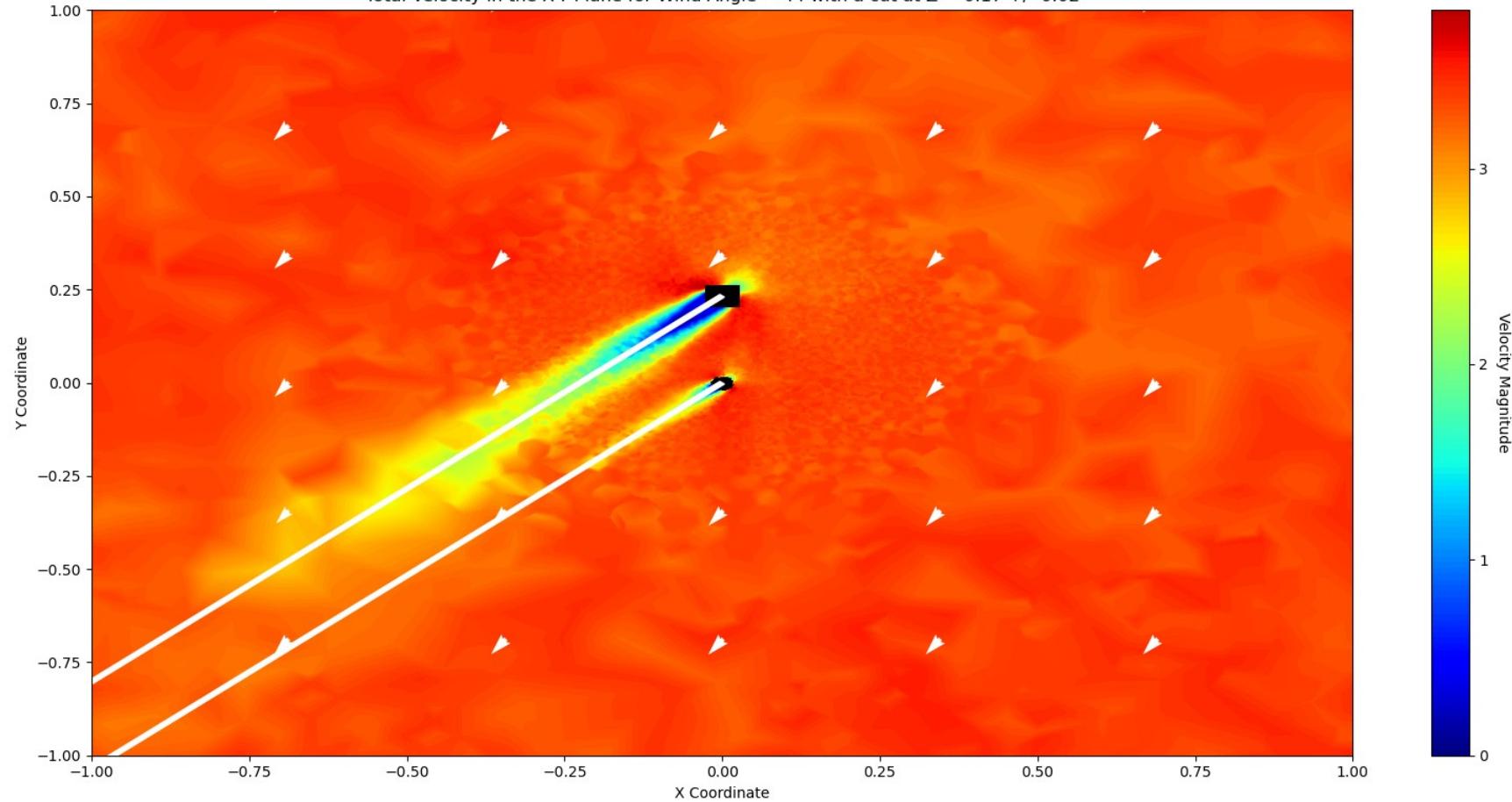
Total Velocity in the X-Y Plane for Wind Angle = 42 with a cut at Z = 0.17 +/- 0.02



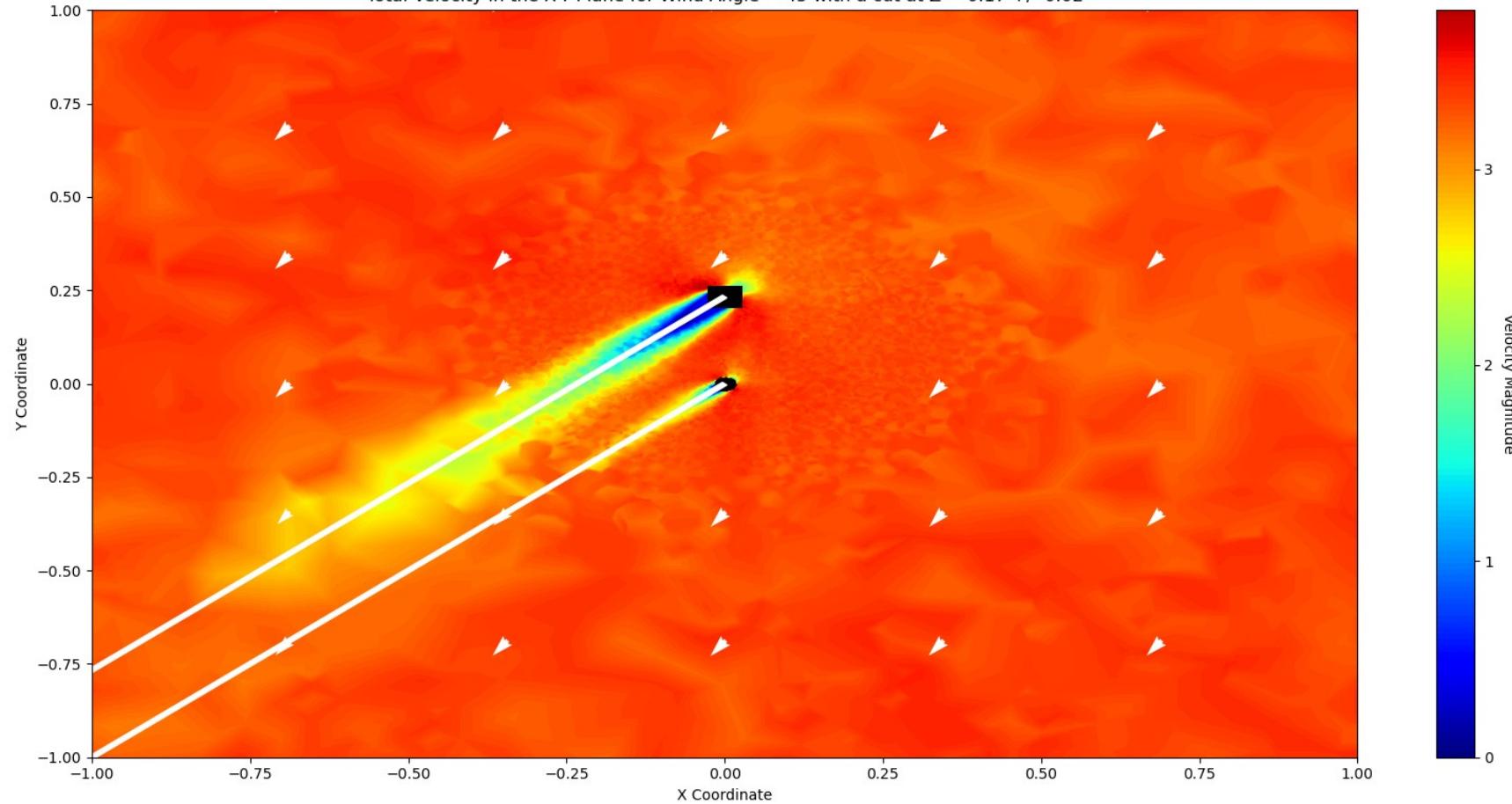
Total Velocity in the X-Y Plane for Wind Angle = 43 with a cut at Z = 0.17 +/- 0.02



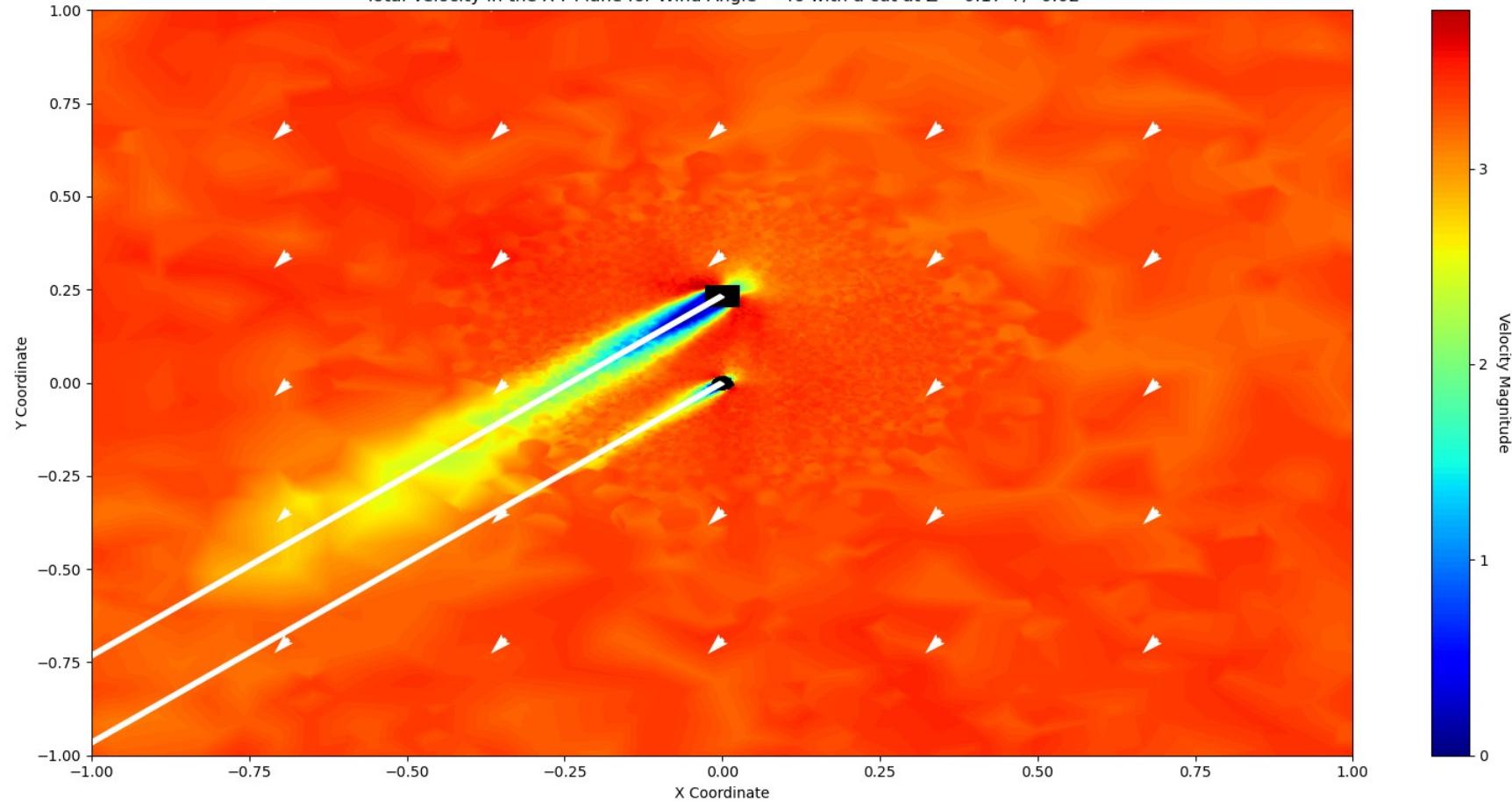
Total Velocity in the X-Y Plane for Wind Angle = 44 with a cut at Z = 0.17 +/- 0.02



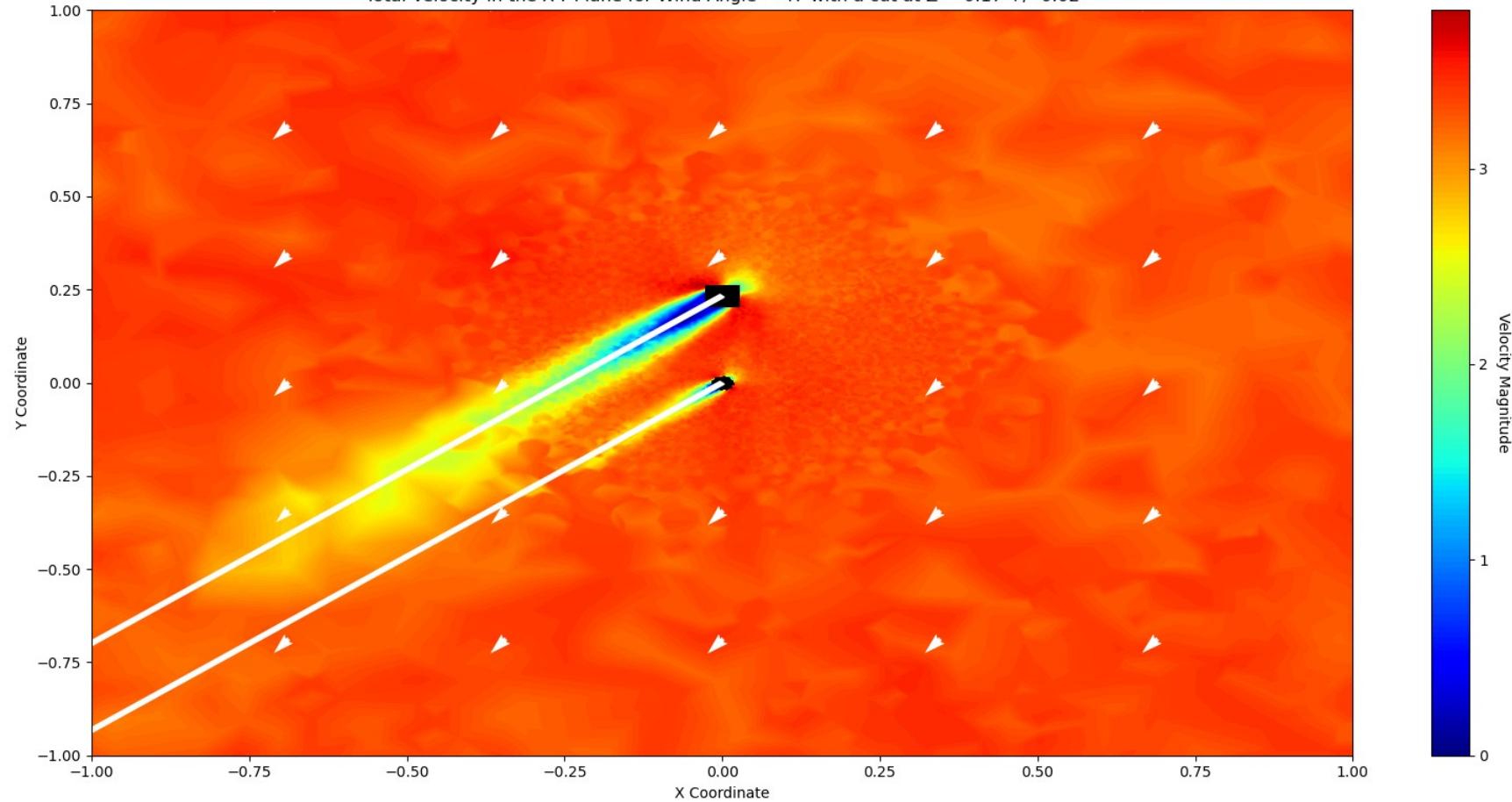
Total Velocity in the X-Y Plane for Wind Angle = 45 with a cut at Z = 0.17 +/- 0.02



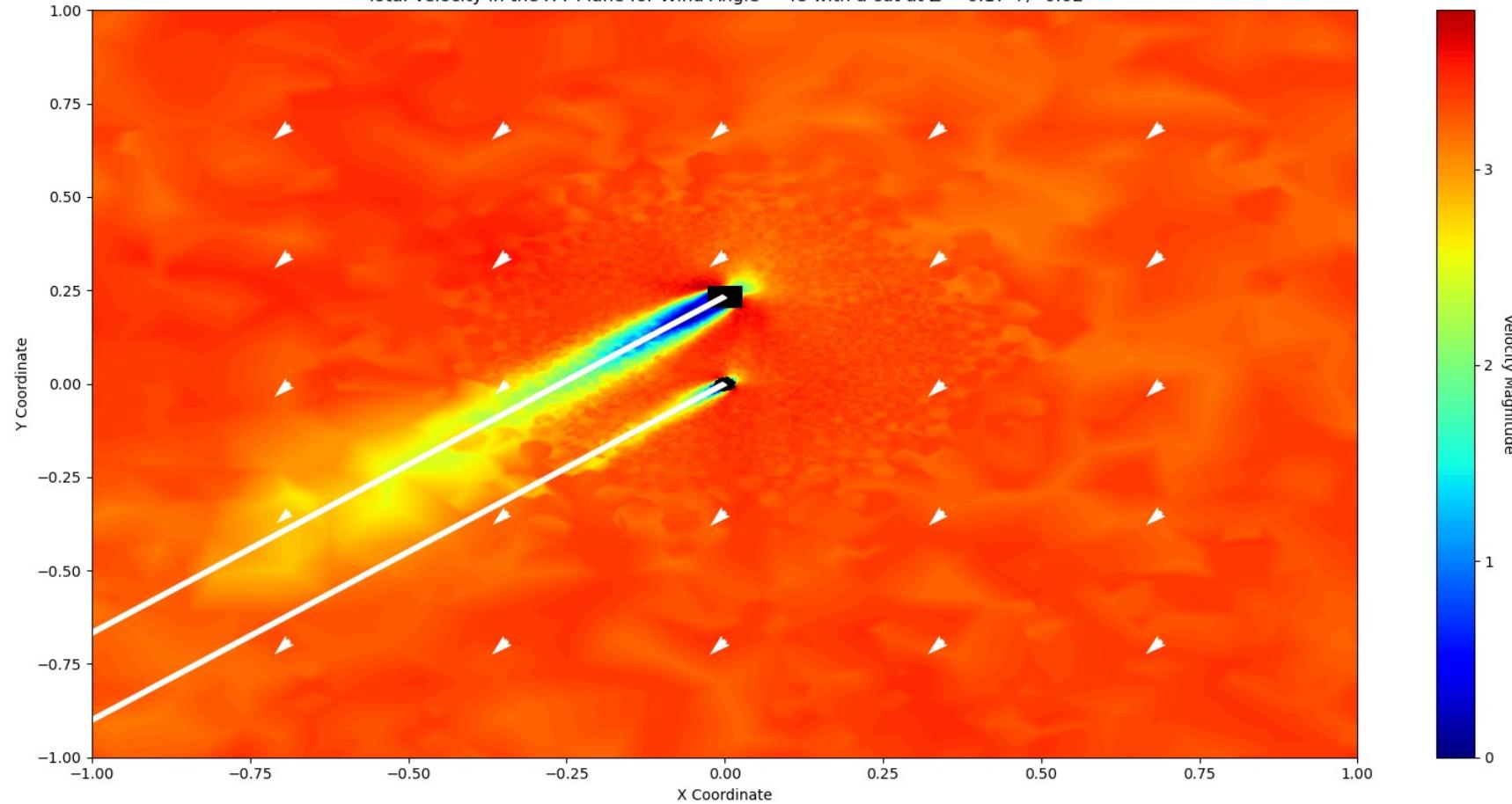
Total Velocity in the X-Y Plane for Wind Angle = 46 with a cut at Z = 0.17 +/- 0.02



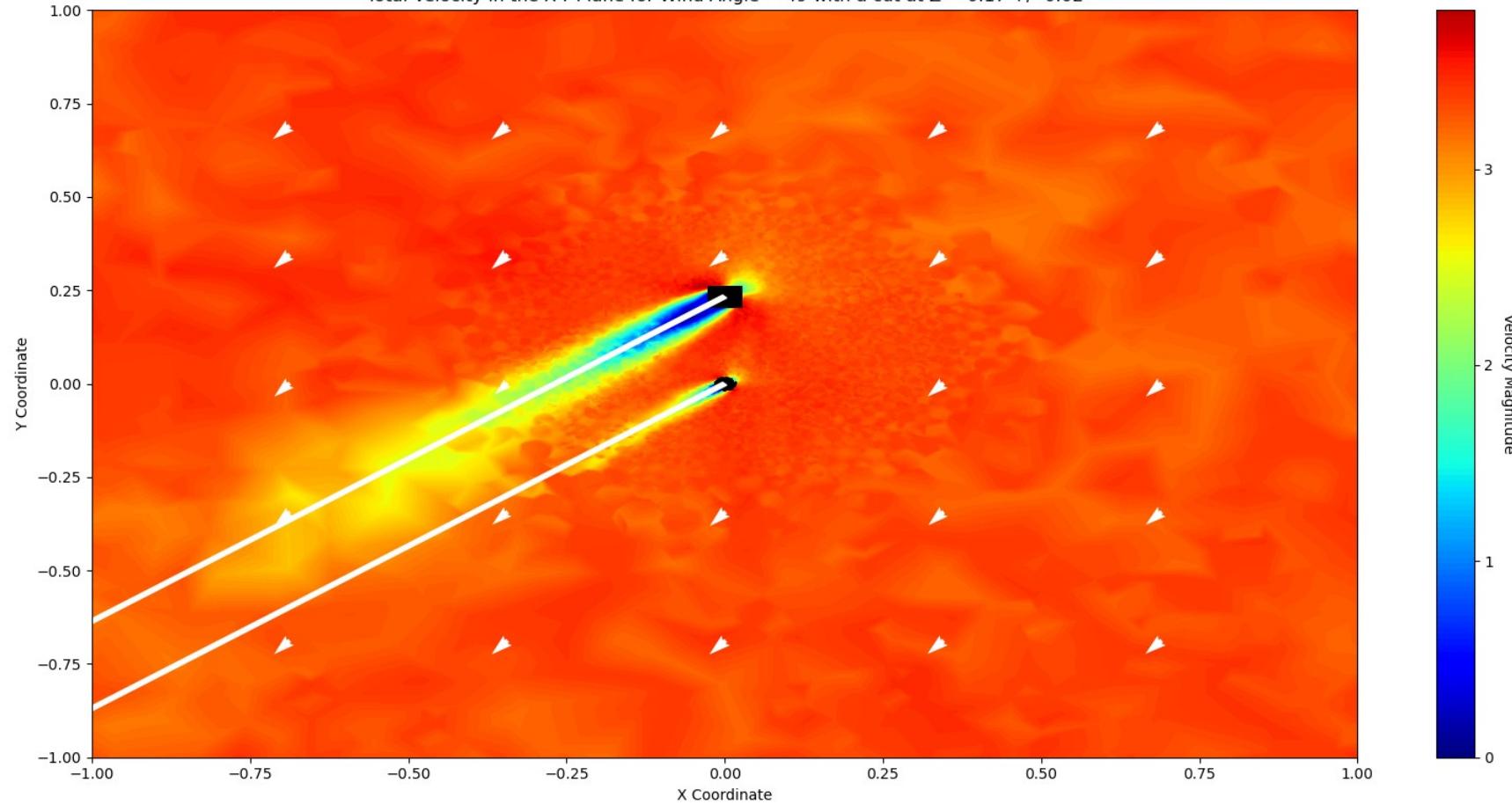
Total Velocity in the X-Y Plane for Wind Angle = 47 with a cut at Z = 0.17 +/- 0.02



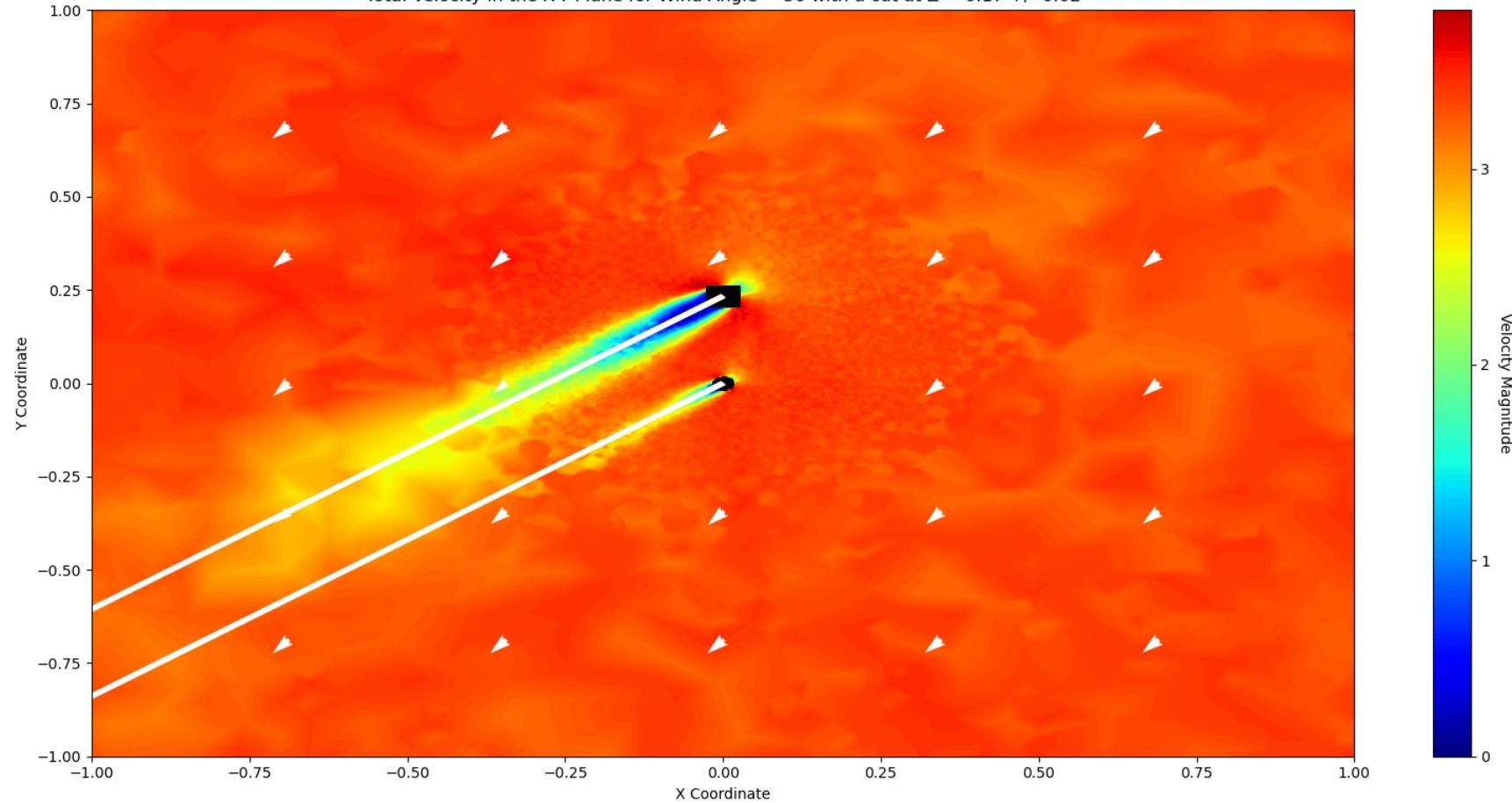
Total Velocity in the X-Y Plane for Wind Angle = 48 with a cut at Z = 0.17 +/- 0.02



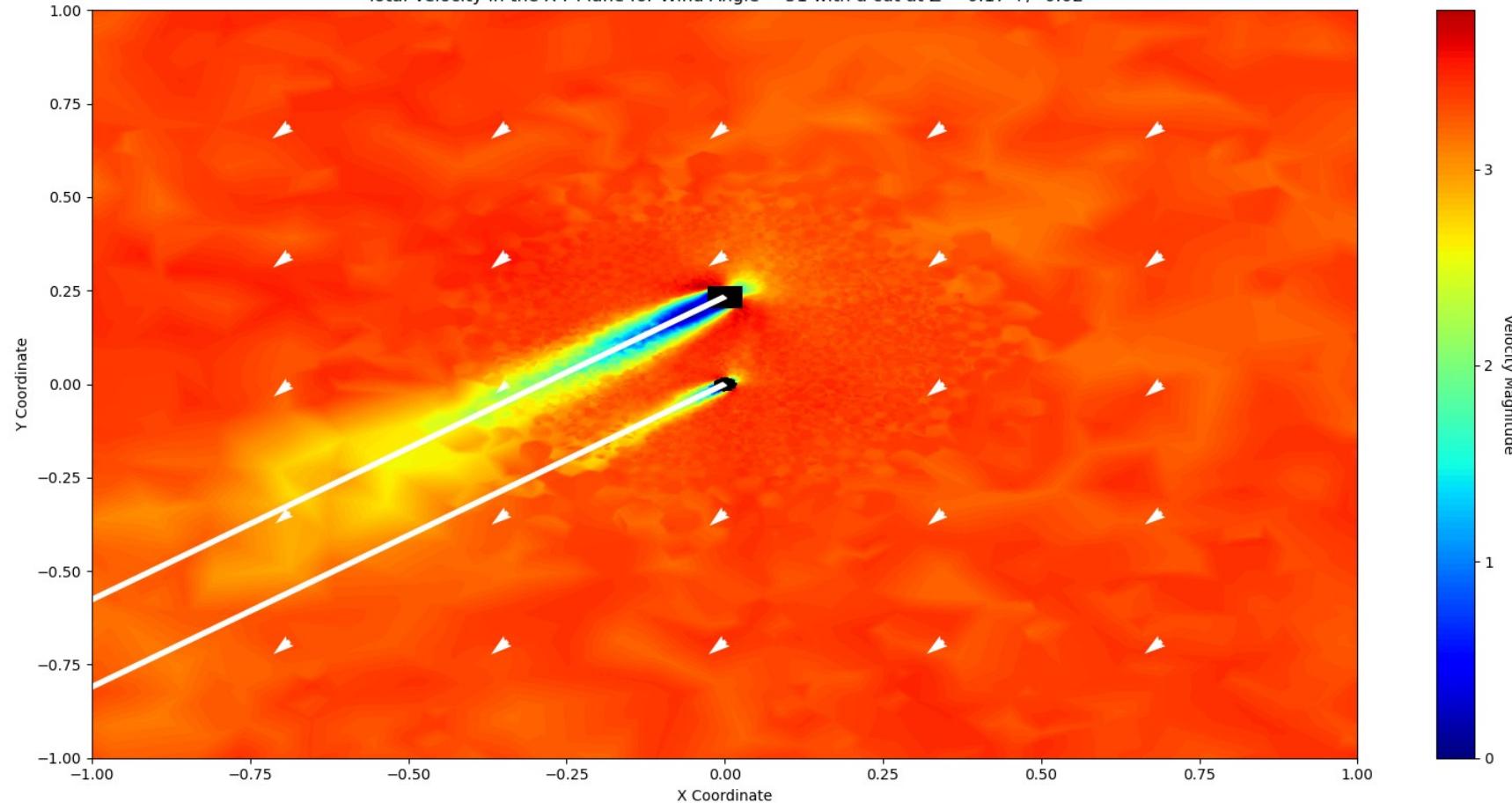
Total Velocity in the X-Y Plane for Wind Angle = 49 with a cut at Z = 0.17 +/- 0.02



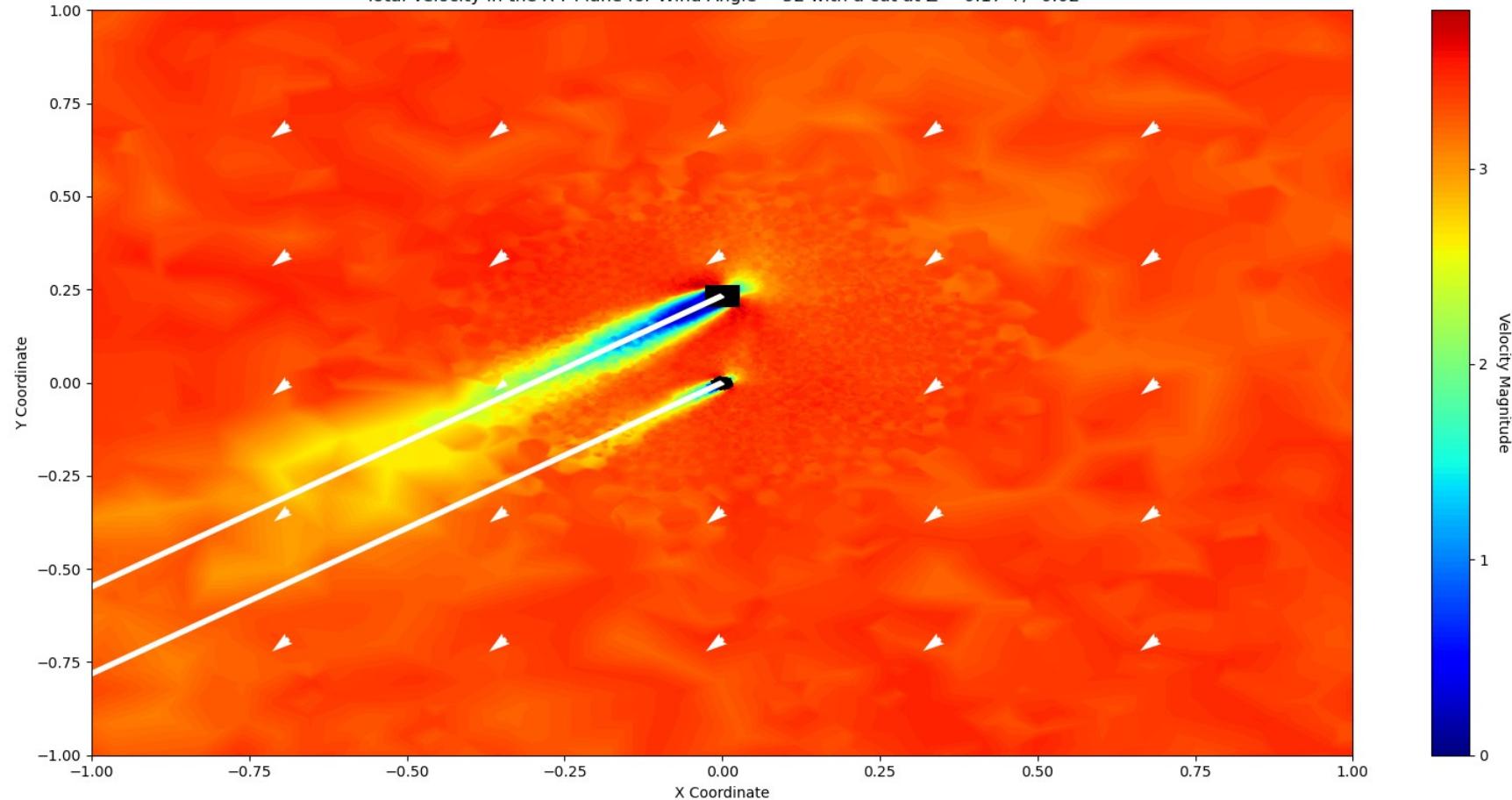
Total Velocity in the X-Y Plane for Wind Angle = 50 with a cut at Z = 0.17 +/- 0.02



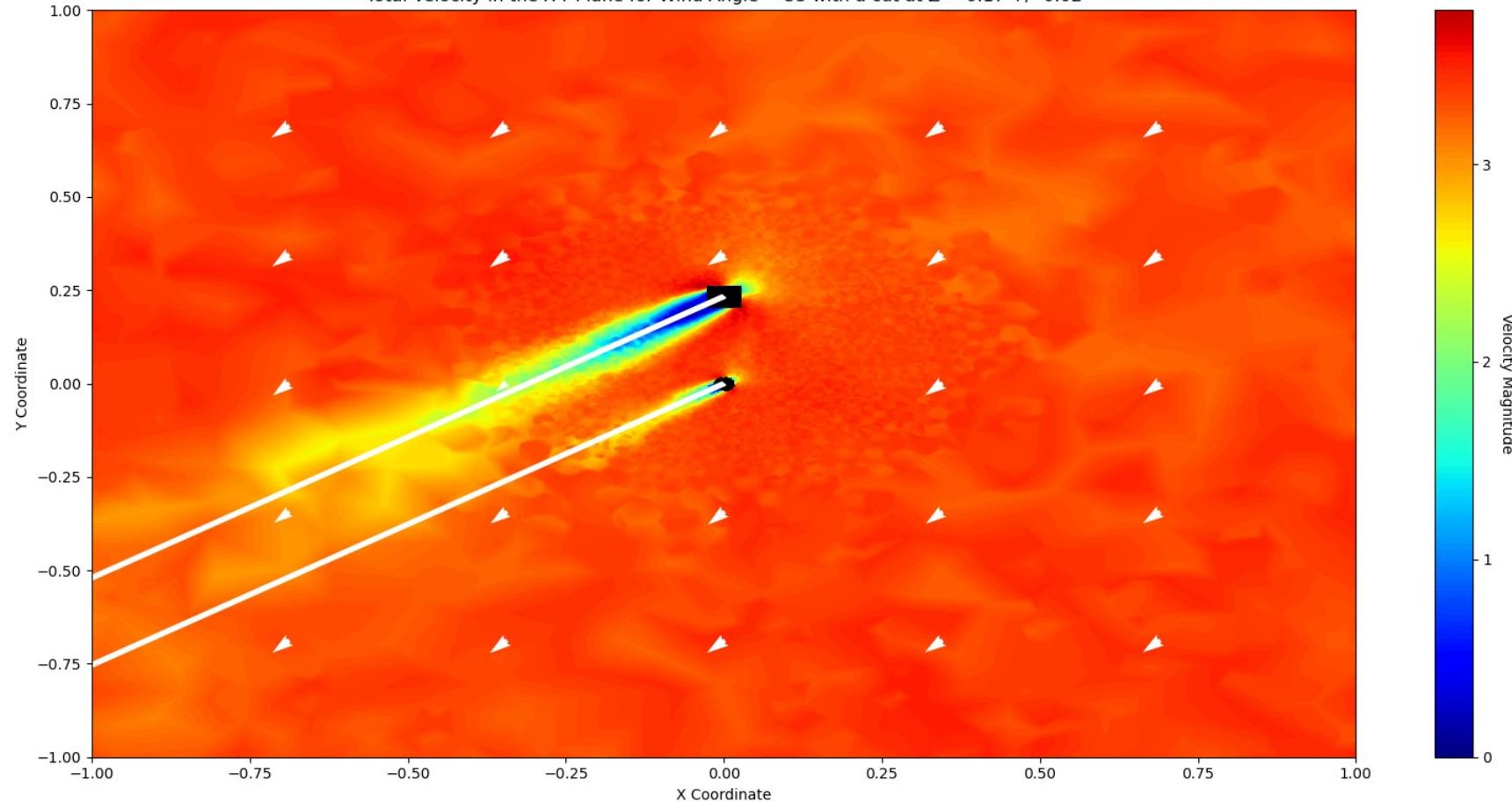
Total Velocity in the X-Y Plane for Wind Angle = 51 with a cut at Z = 0.17 +/- 0.02



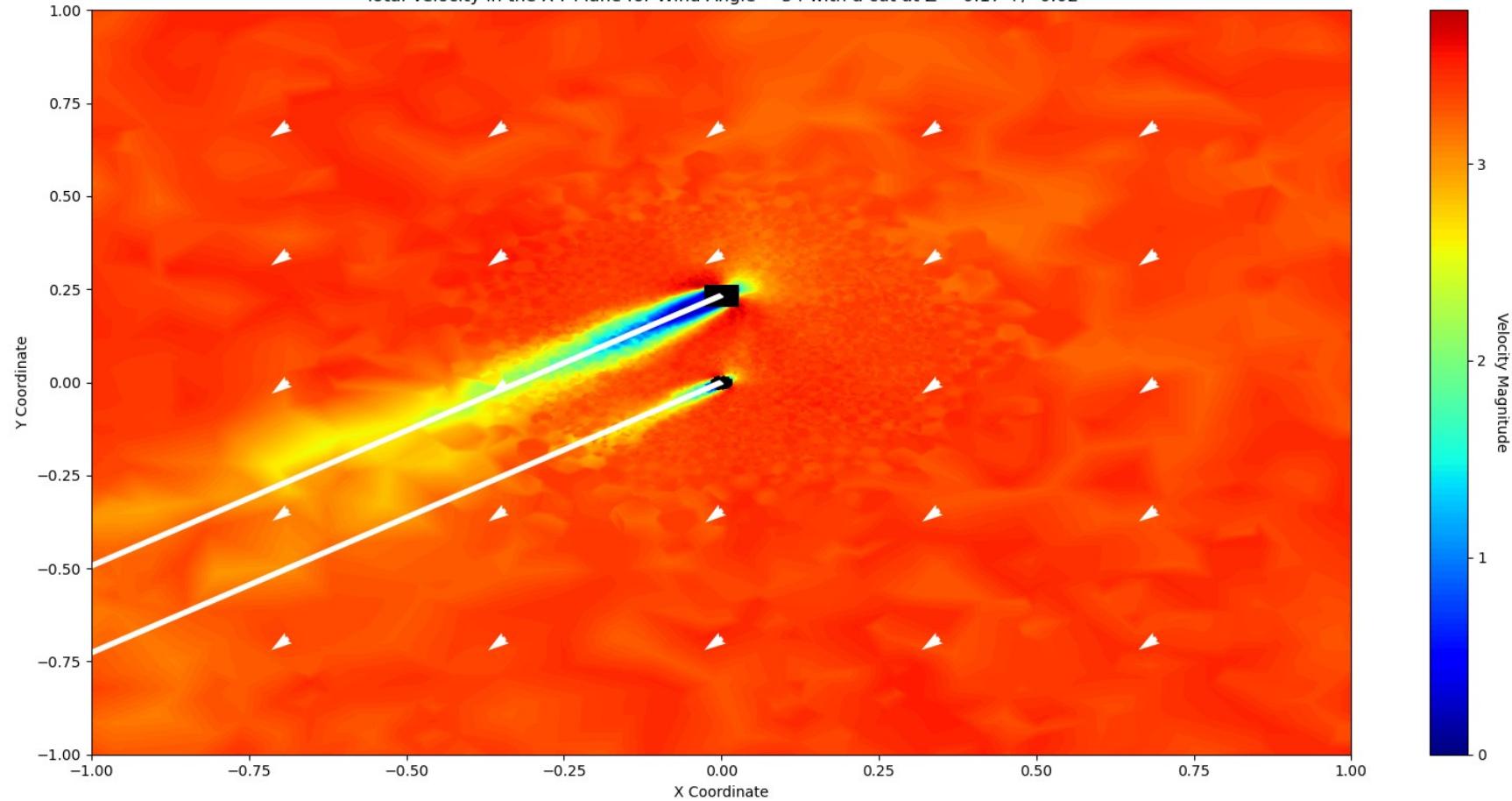
Total Velocity in the X-Y Plane for Wind Angle = 52 with a cut at Z = 0.17 +/- 0.02



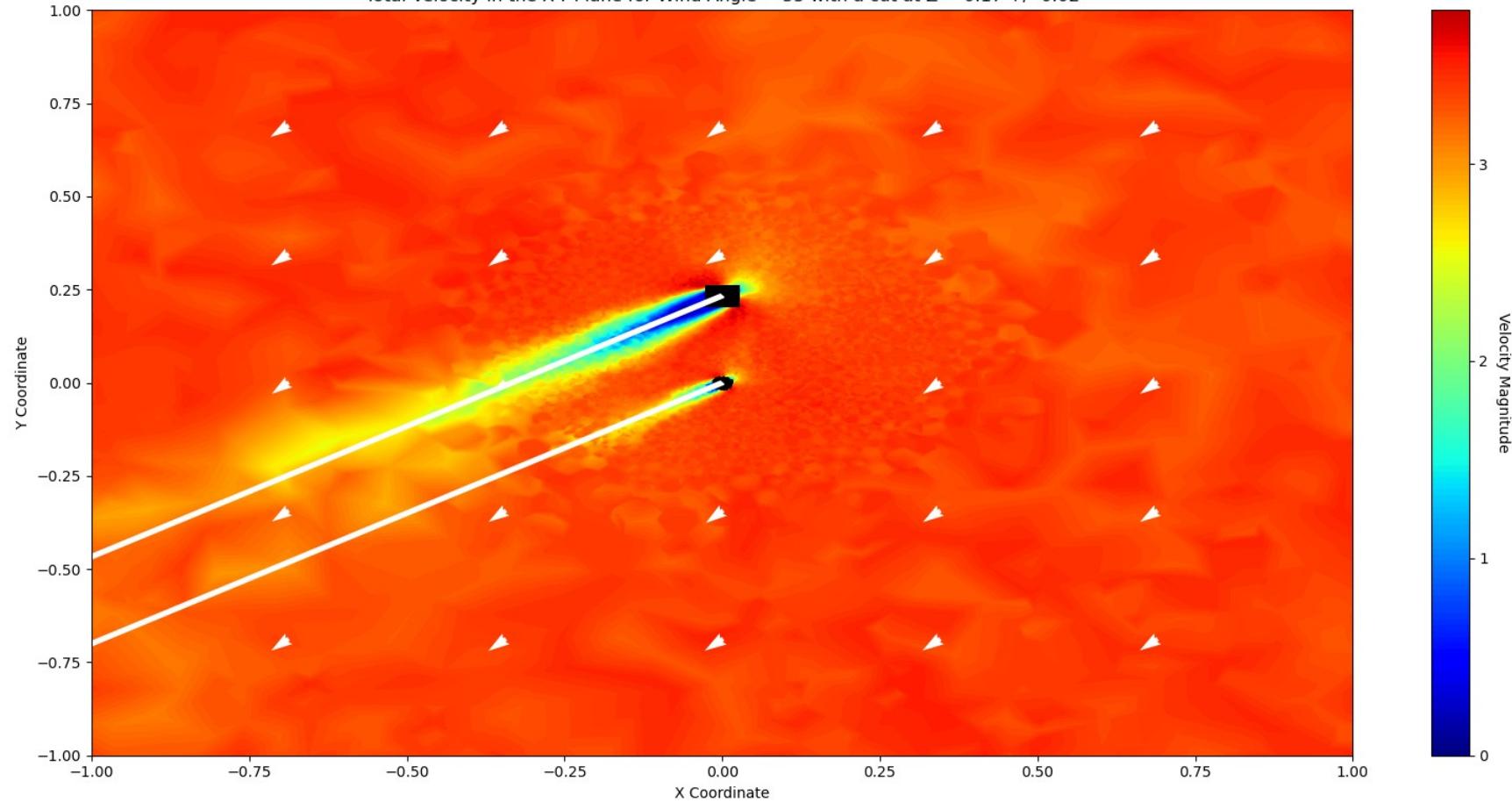
Total Velocity in the X-Y Plane for Wind Angle = 53 with a cut at Z = 0.17 +/- 0.02



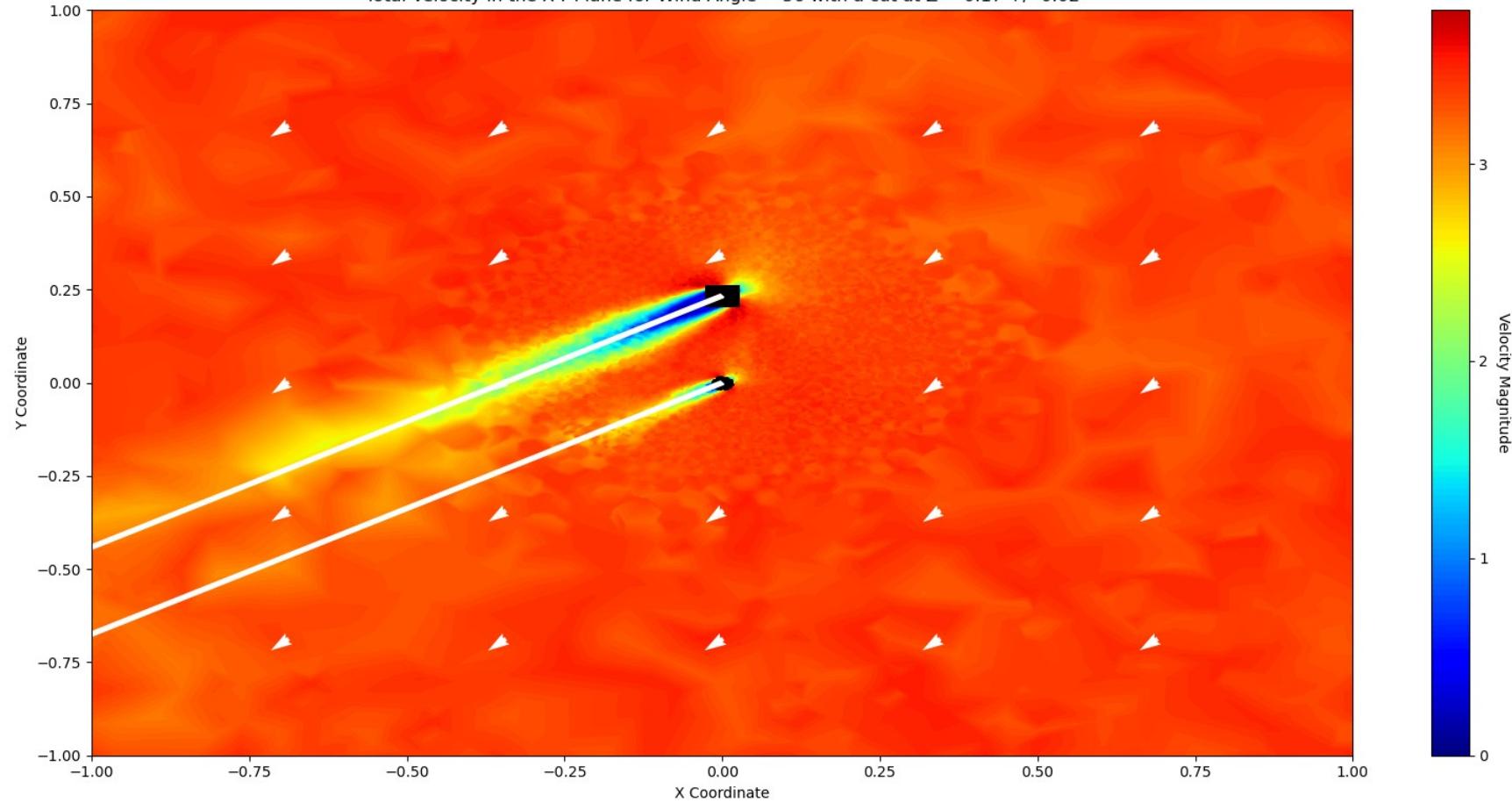
Total Velocity in the X-Y Plane for Wind Angle = 54 with a cut at Z = 0.17 +/- 0.02



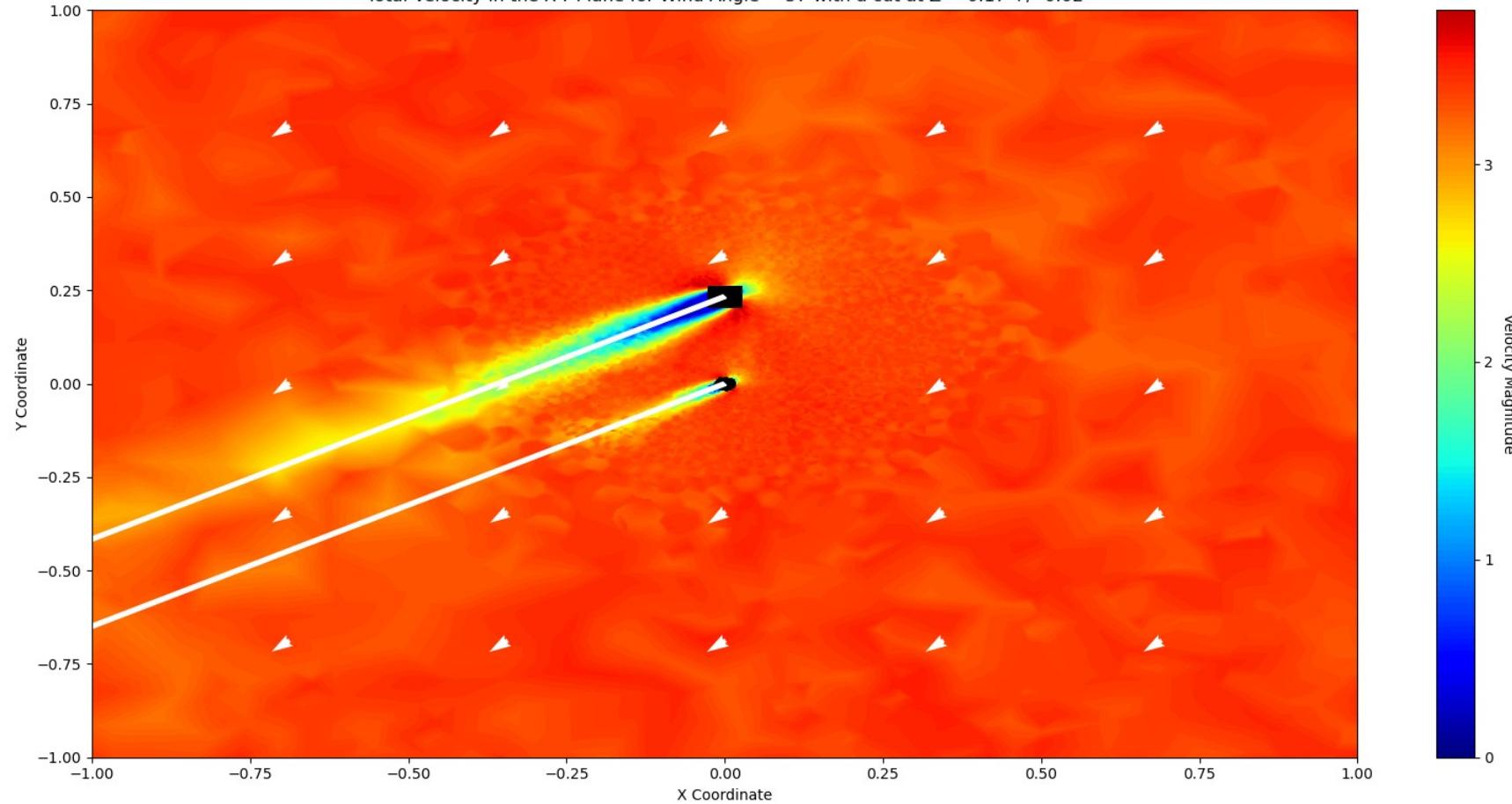
Total Velocity in the X-Y Plane for Wind Angle = 55 with a cut at Z = 0.17 +/- 0.02



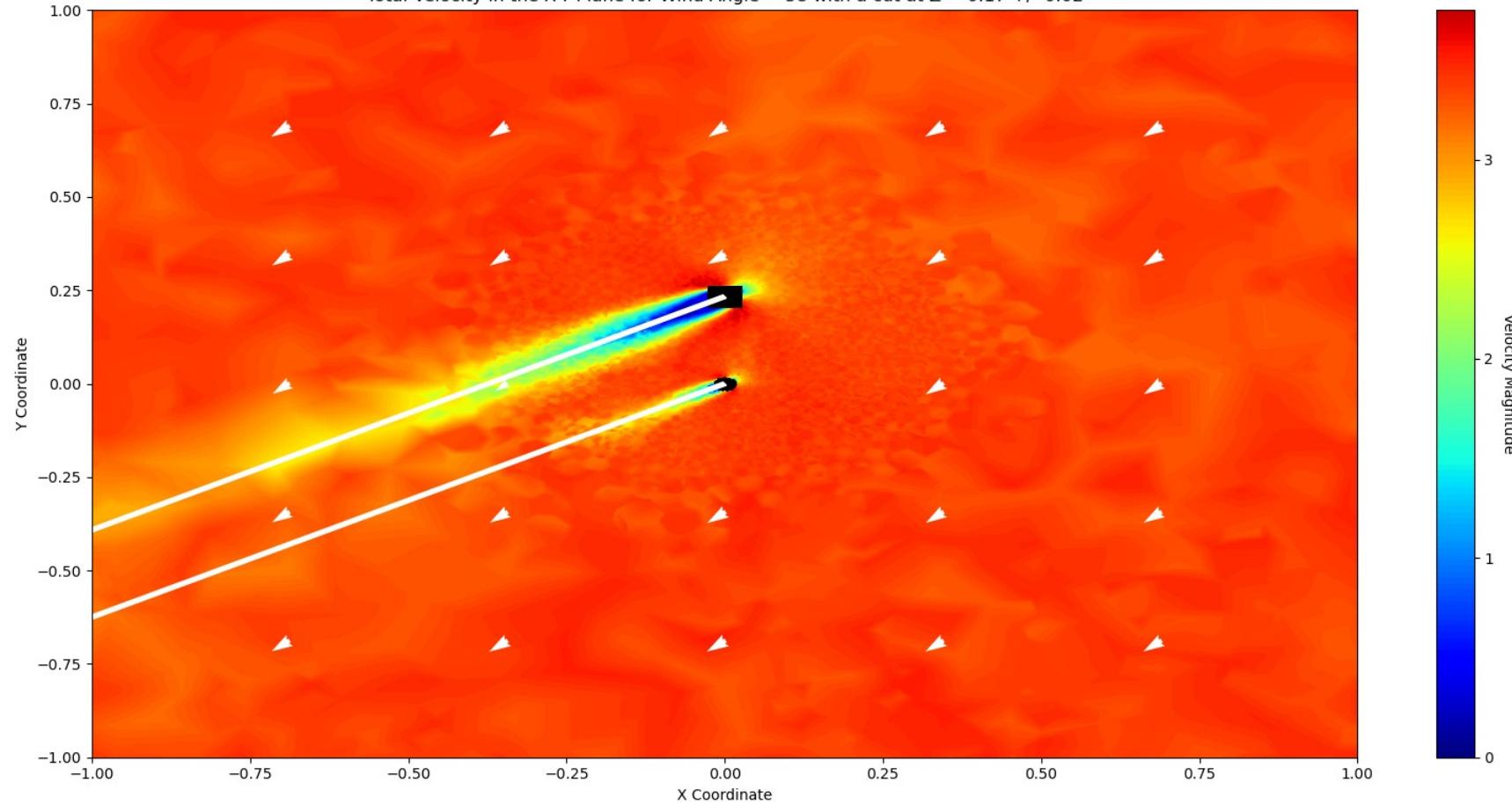
Total Velocity in the X-Y Plane for Wind Angle = 56 with a cut at Z = 0.17 +/- 0.02



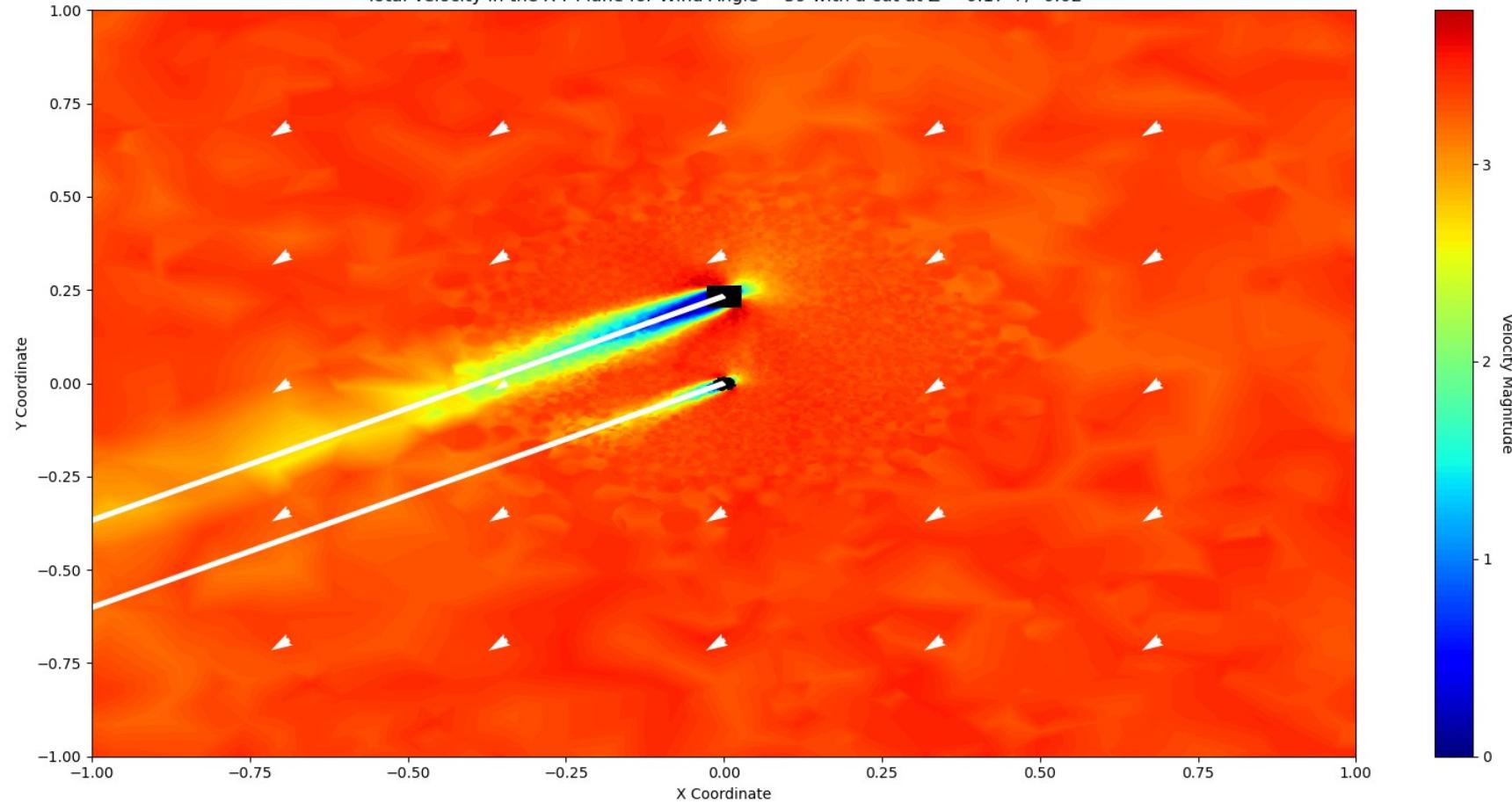
Total Velocity in the X-Y Plane for Wind Angle = 57 with a cut at Z = 0.17 +/- 0.02



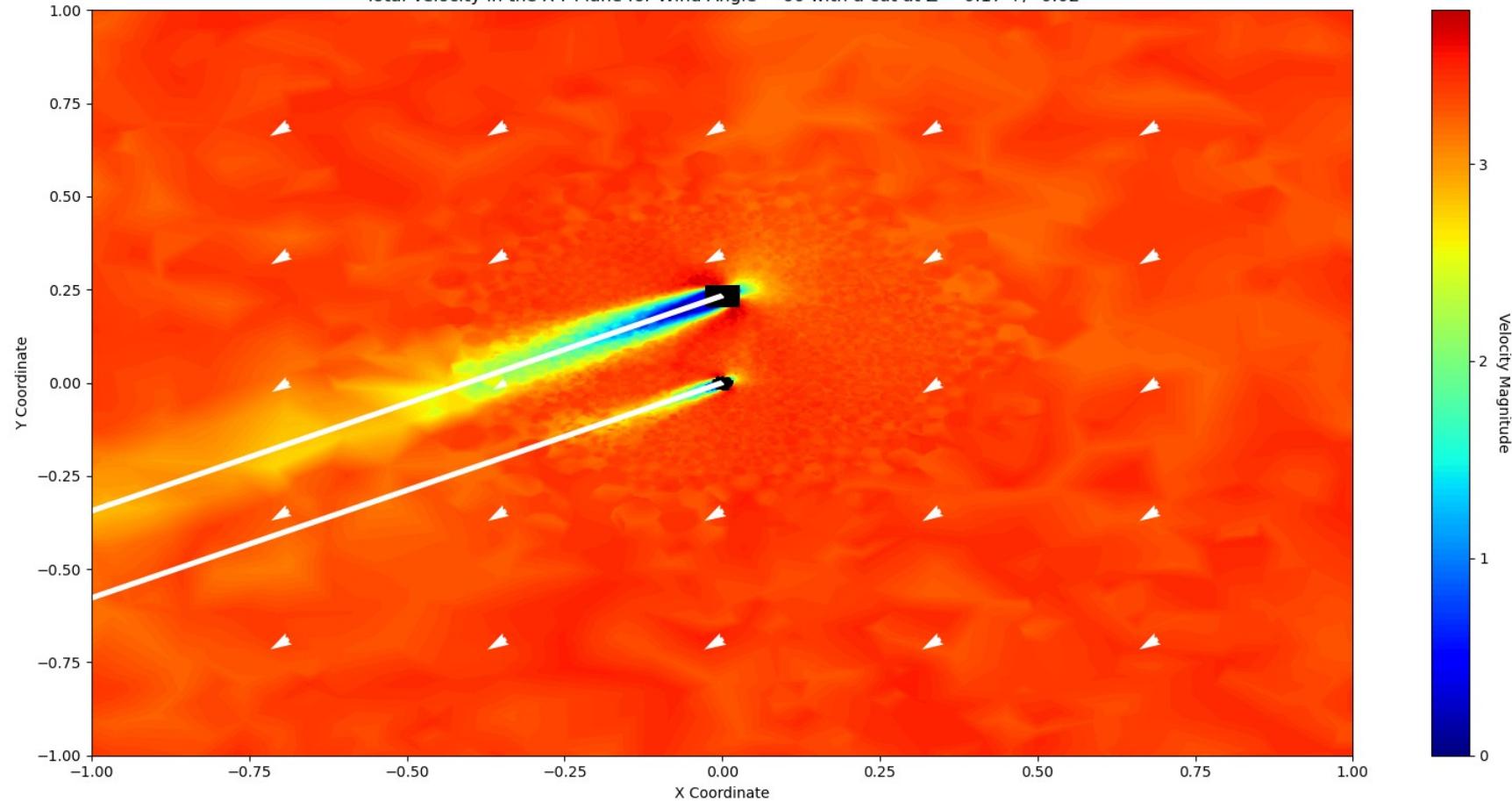
Total Velocity in the X-Y Plane for Wind Angle = 58 with a cut at Z = 0.17 +/- 0.02



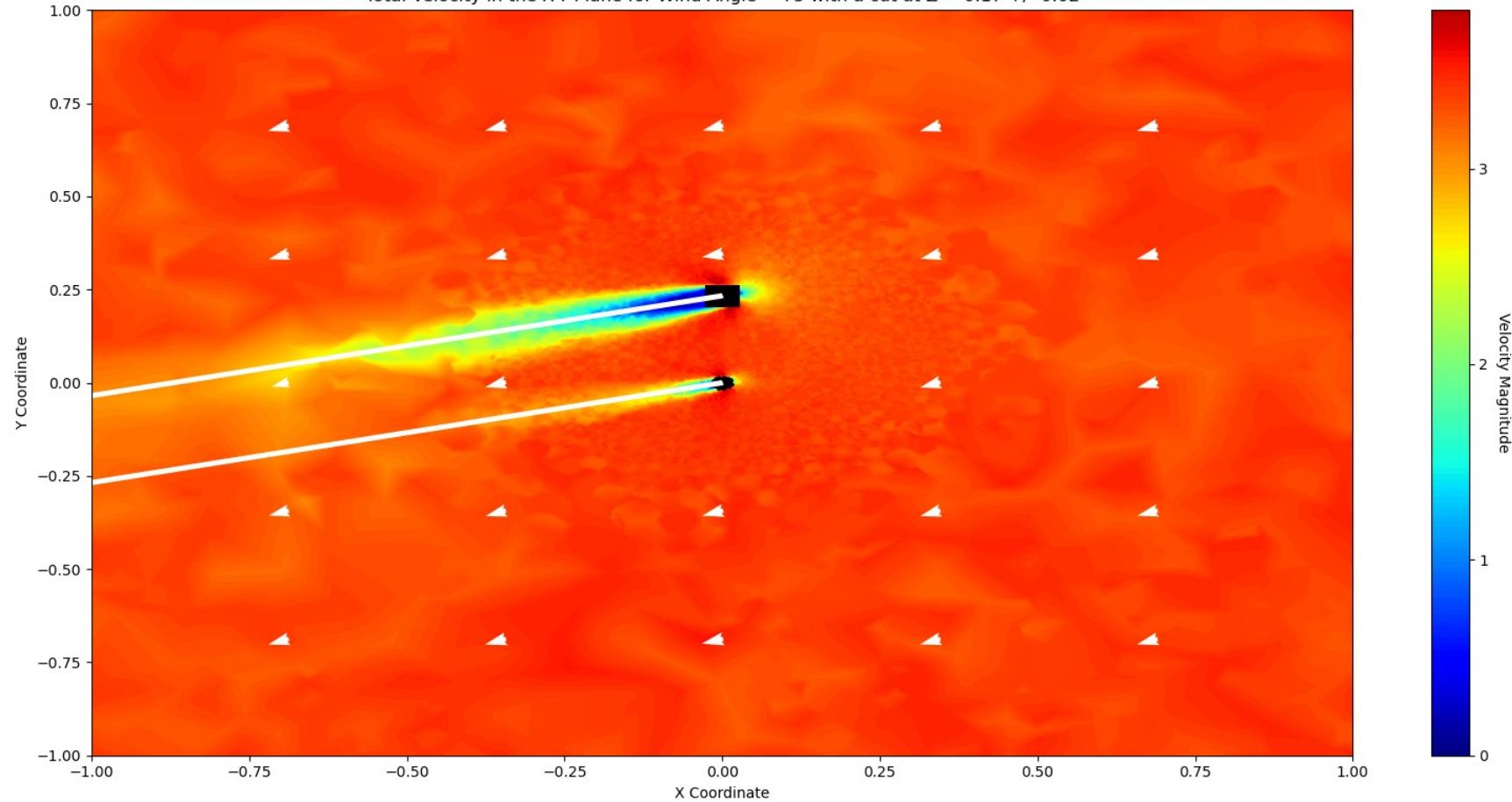
Total Velocity in the X-Y Plane for Wind Angle = 59 with a cut at Z = 0.17 +/- 0.02



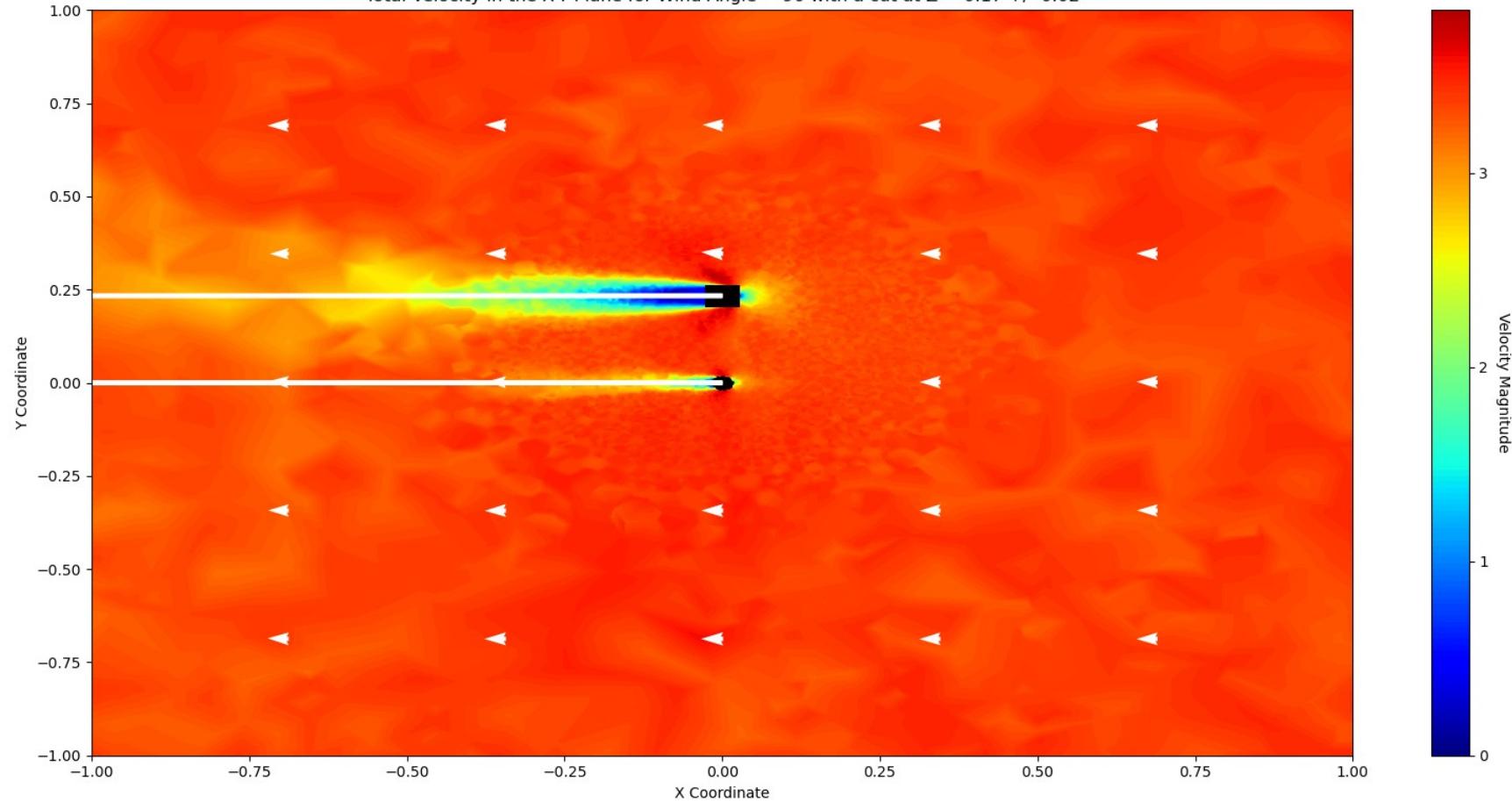
Total Velocity in the X-Y Plane for Wind Angle = 60 with a cut at Z = 0.17 +/- 0.02



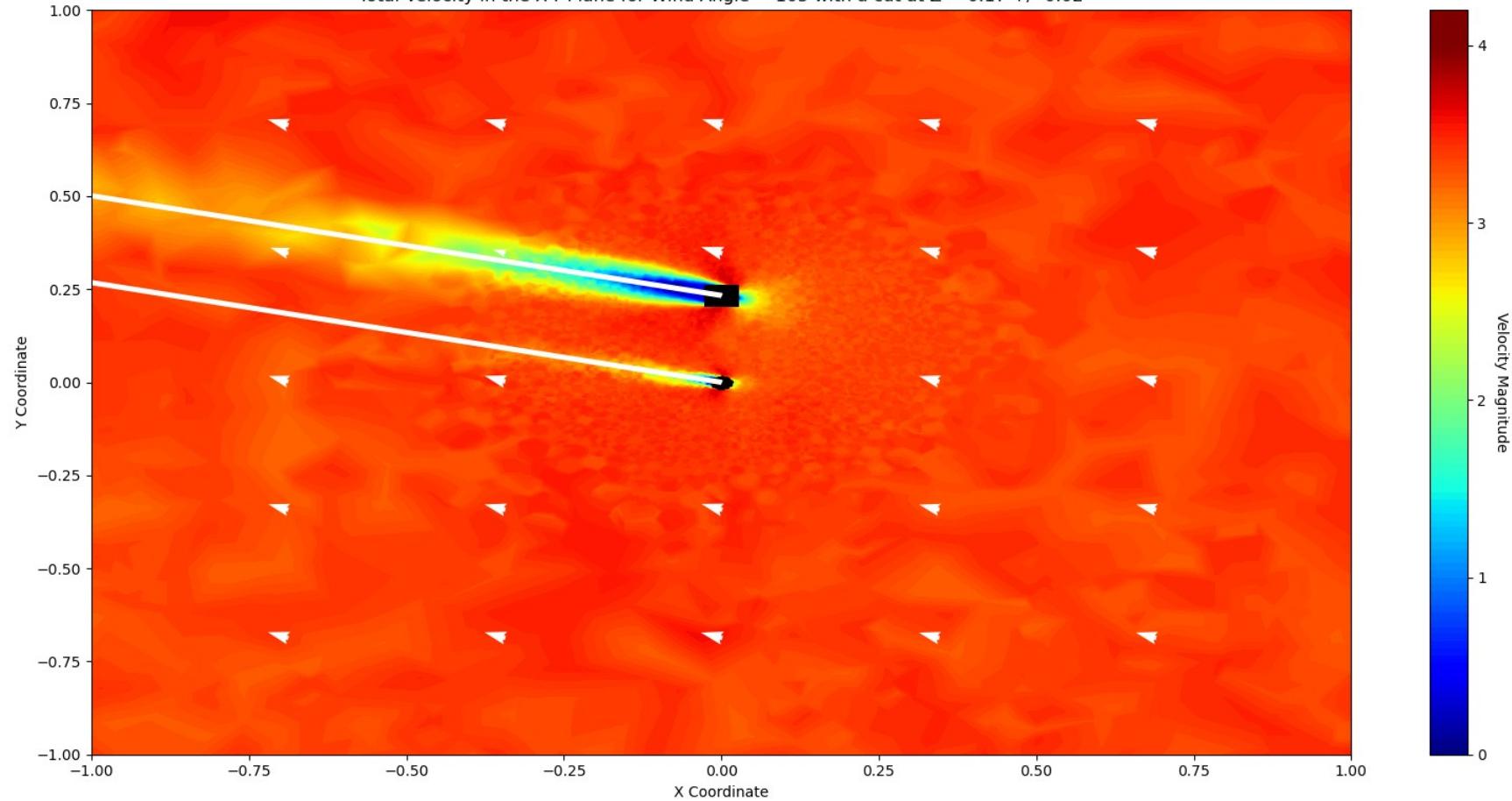
Total Velocity in the X-Y Plane for Wind Angle = 75 with a cut at Z = 0.17 +/- 0.02



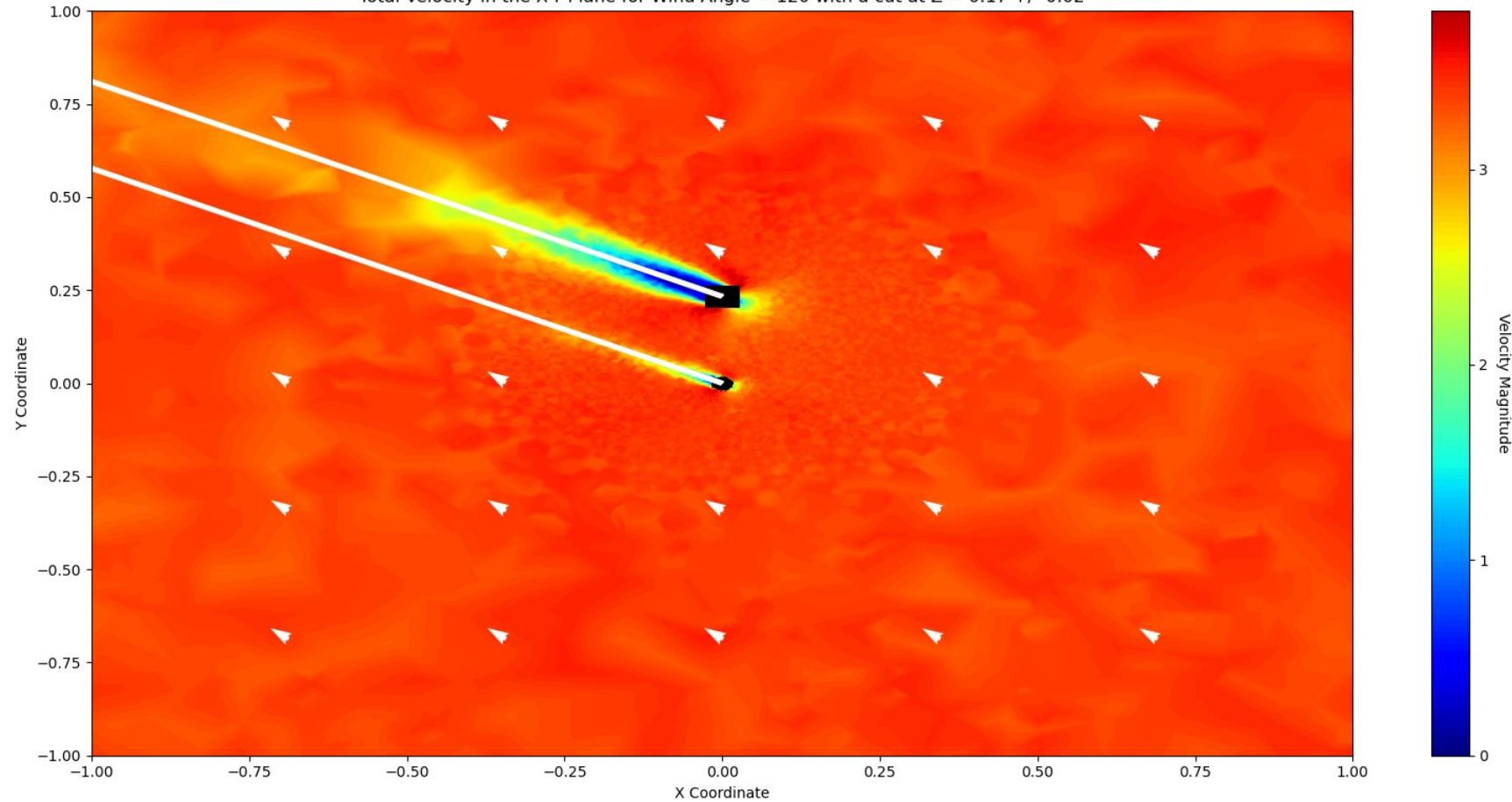
Total Velocity in the X-Y Plane for Wind Angle = 90 with a cut at Z = 0.17 +/- 0.02



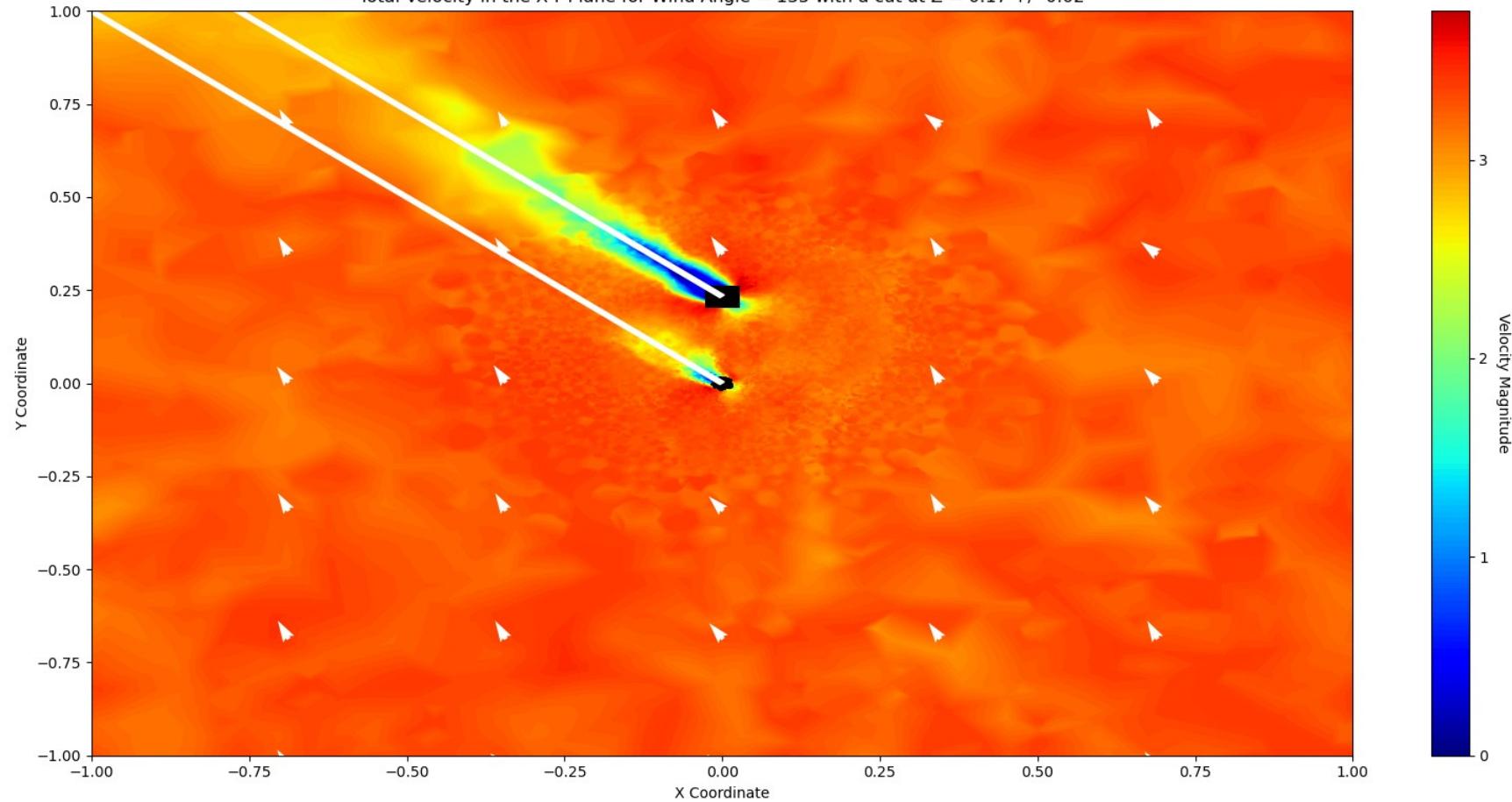
Total Velocity in the X-Y Plane for Wind Angle = 105 with a cut at Z = 0.17 +/- 0.02



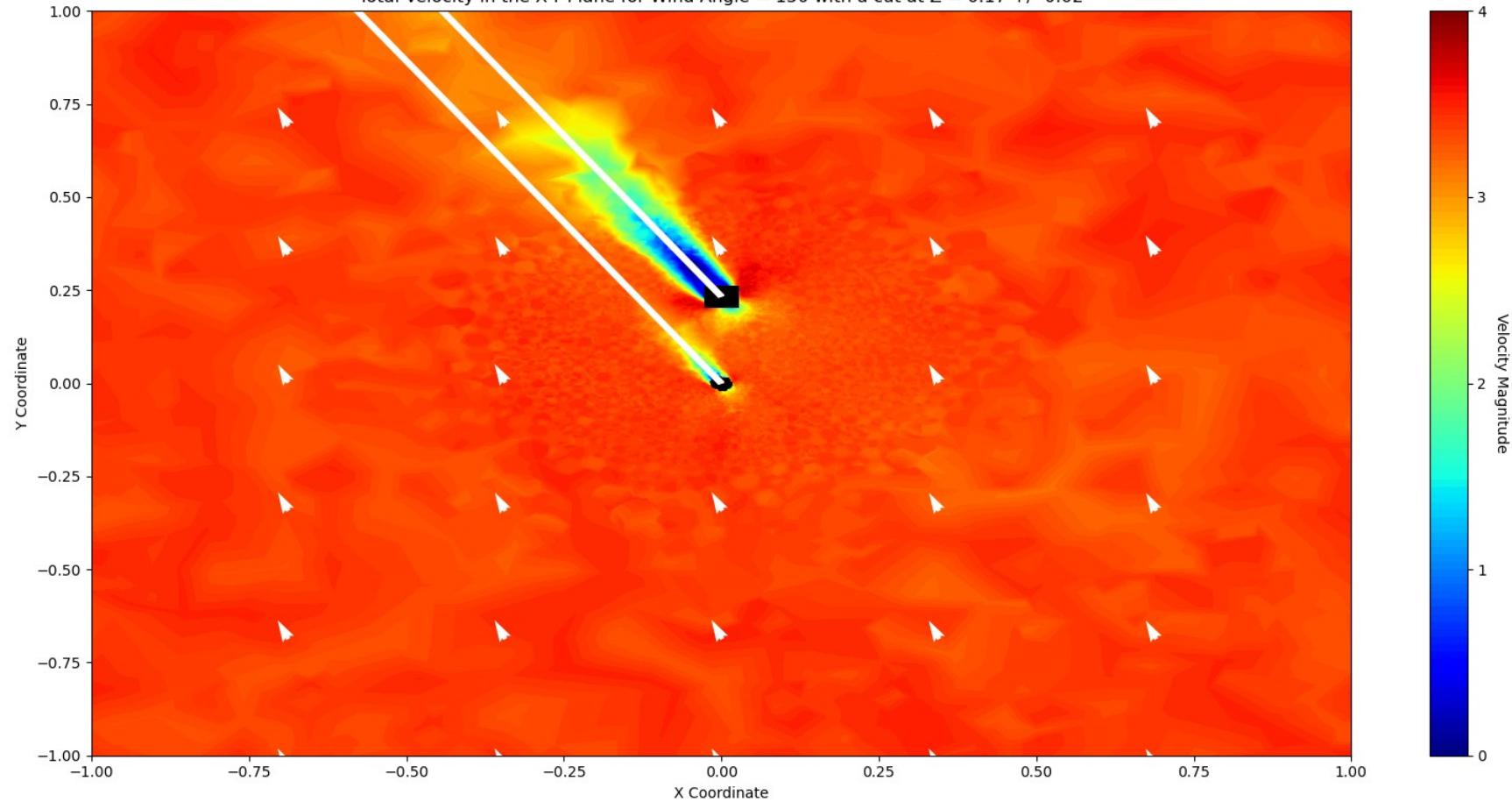
Total Velocity in the X-Y Plane for Wind Angle = 120 with a cut at Z = 0.17 +/- 0.02



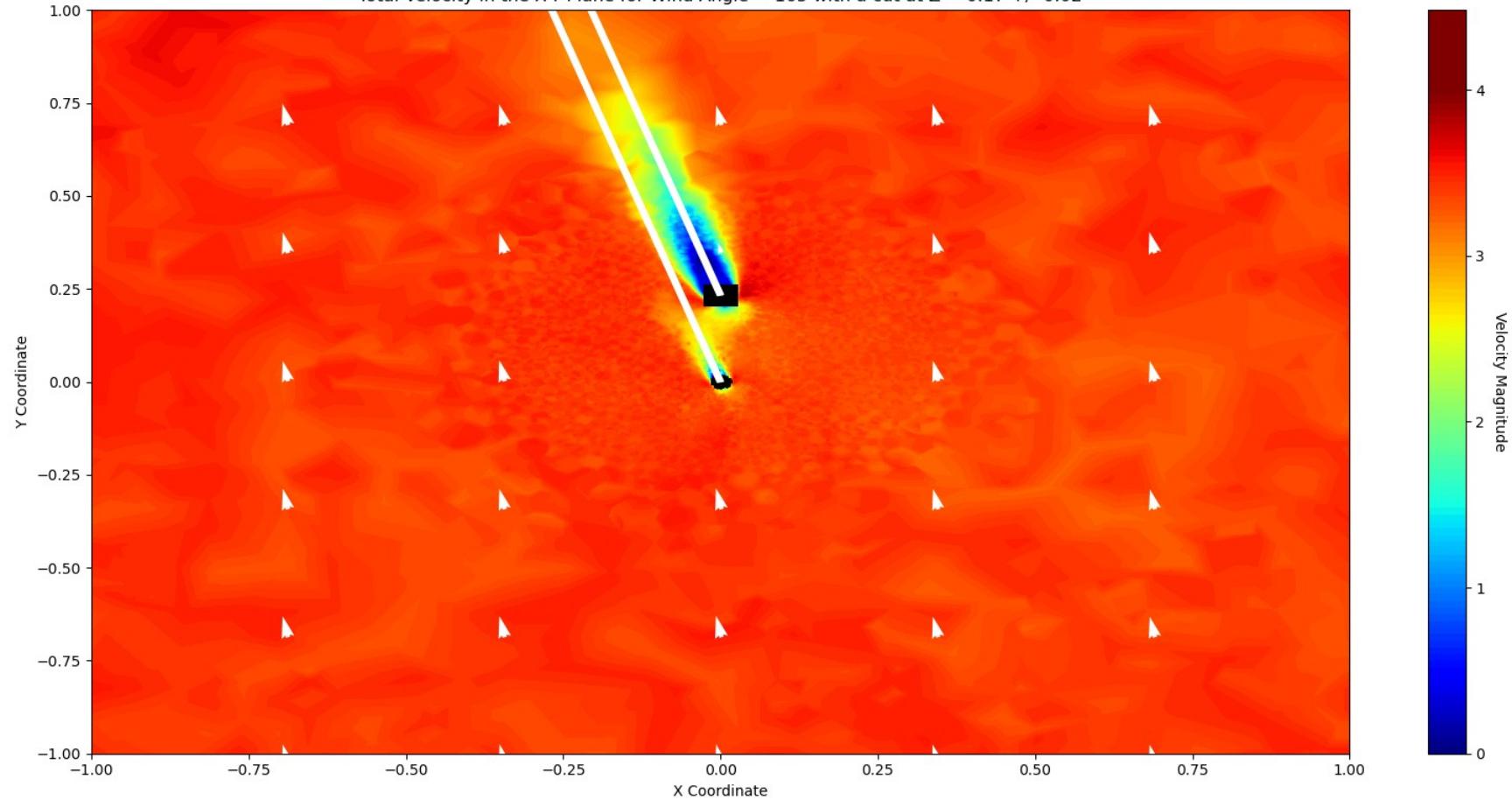
Total Velocity in the X-Y Plane for Wind Angle = 135 with a cut at Z = 0.17 +/- 0.02



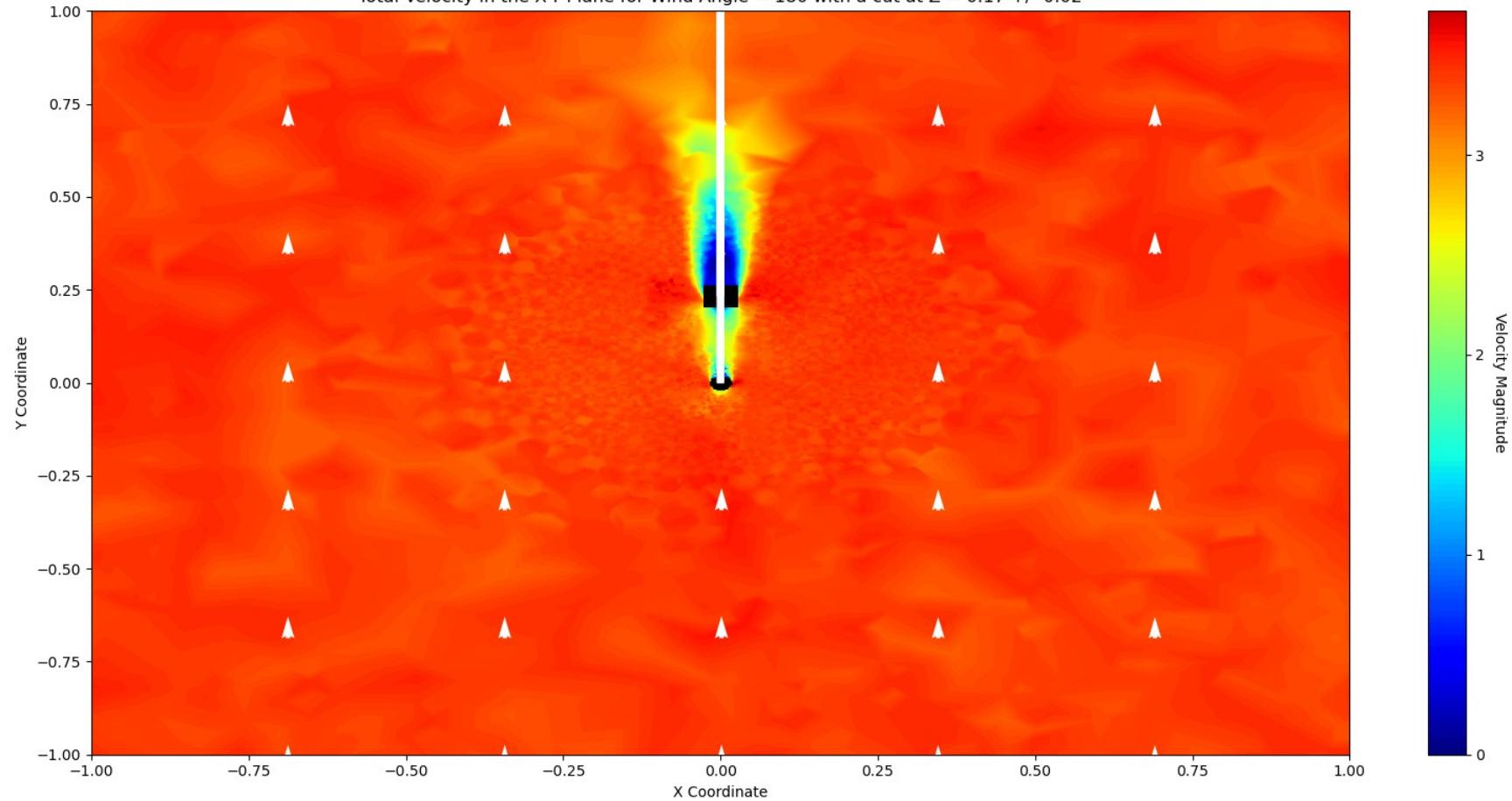
Total Velocity in the X-Y Plane for Wind Angle = 150 with a cut at Z = 0.17 +/- 0.02



Total Velocity in the X-Y Plane for Wind Angle = 165 with a cut at Z = 0.17 +/- 0.02



Total Velocity in the X-Y Plane for Wind Angle = 180 with a cut at Z = 0.17 +/- 0.02



Scripts v3 – Preliminary Results

Some Parameters

Infinite epochs - instead the criteria for stopping is $\text{loss}_{\{n\}} - \text{loss}_{\{n-1\}} < \varepsilon$ for 10 consecutive epochs where n is the epoch number and $\varepsilon = 1E-5$ (user defined)

128 Neurons for the PINN unless otherwise specified

We have the data for 8 angles, [0, 30, 60, 90, 120, 135, 150, 180] in degrees

We concatenate the data for angles = [0, 30, 60, 90, 120, 150, 180] and then take 99.99% of the dataset with random seed = 42 for training and 0.01% for testing

By using the whole dataset we hope to make the NN learn about wind angle such that the parameters become functions of the wind angle

Then using the trained neural network we predict the data for angle = 135

Progress so far - Data Loss Only
Standard Normal Scalar
(Adam Optimizer)

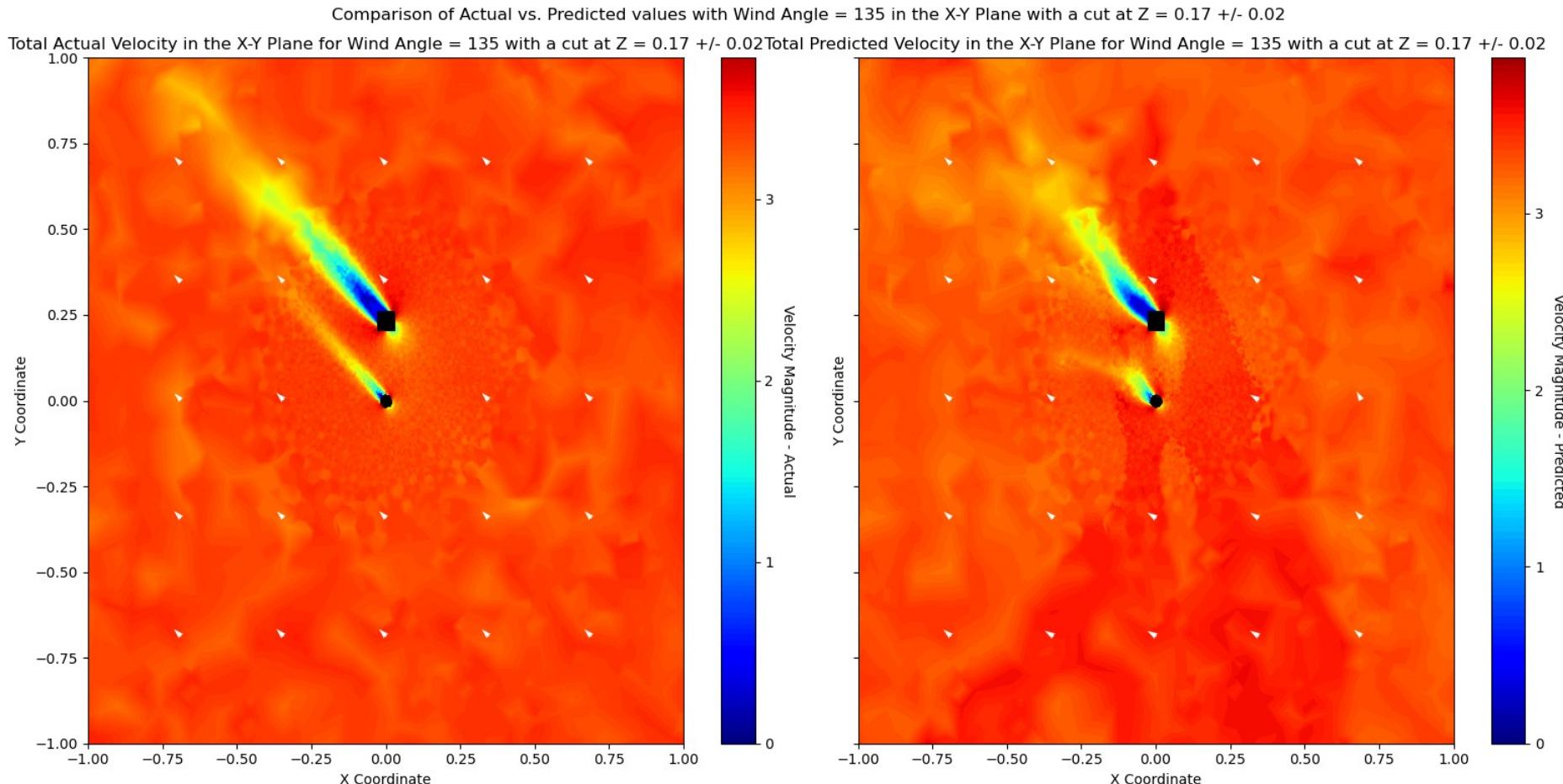
Threshold = 1E-5 (47325 Epochs, not completed), GPU Laptop

Scripts v3 – PREDICTING (135 DEG)

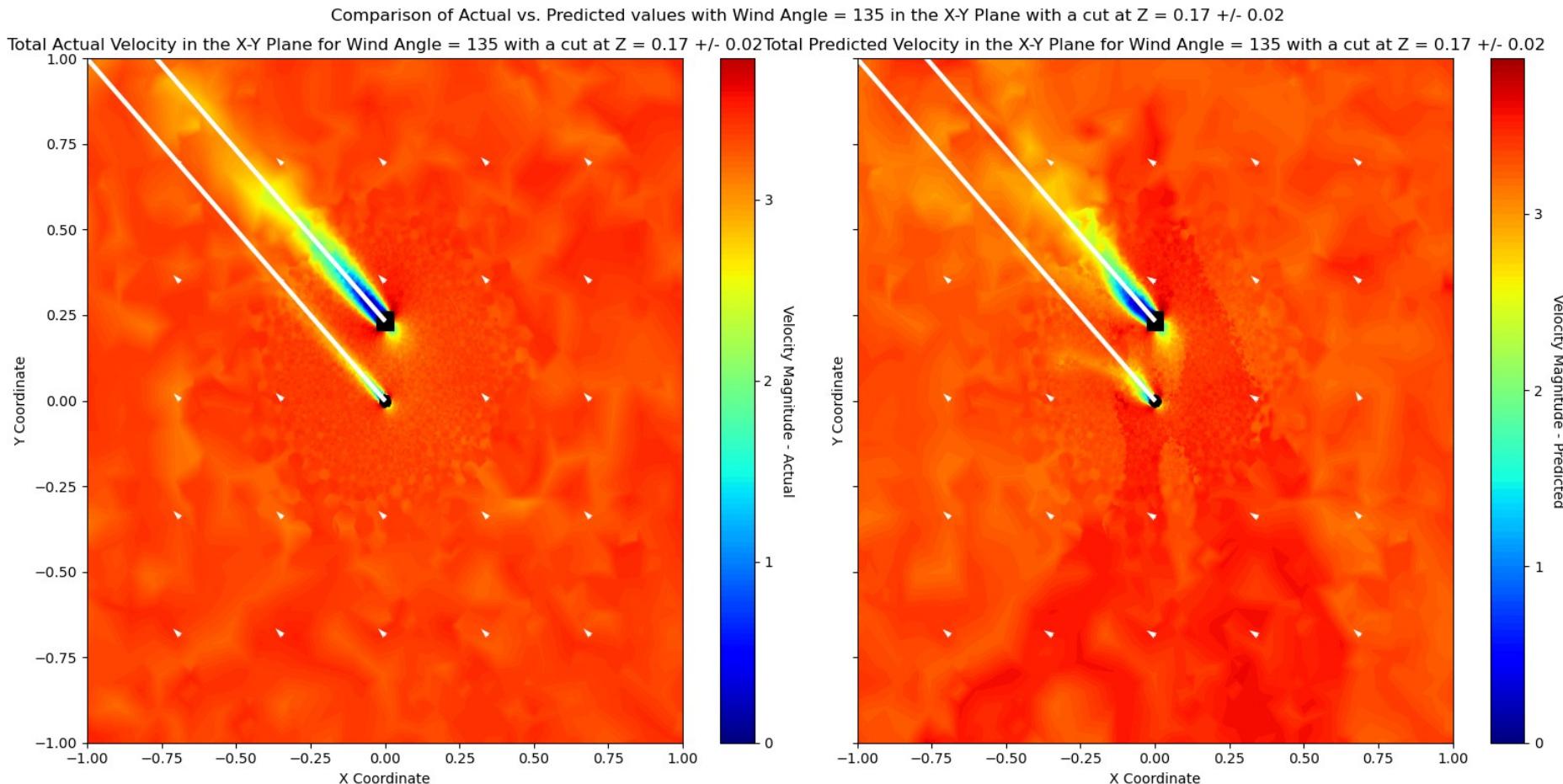
Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar)
Threshold = 1E-5 (47325 Epochs, so far...), GPU Laptop
Predicting Results – Metrics (Angle = 135)

Variable	MSE	RMSE	MAE	R2
Pressure	0.948246457957483	0.97377947090575	0.920350043365719	0.439027703607057
Velocity:0	0.293232083762155	0.541509080036664	0.472882641636198	0.712299594951694
Velocity:1	0.24891062430059	0.498909434968502	0.429775334017177	0.758113233456252
Velocity:2	0.00256477188247639	0.0506435769123429	0.021786293402989	0.921600318662495
TurbVisc	0.201503935569927	0.448891897420667	0.335290029572579	0.998531648004273

Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar), Threshold = 1E-5 (47325 Epochs, so far...), GPU Laptop
Predicting Results - X-Y Total Velocity Plot (Angle = 135)

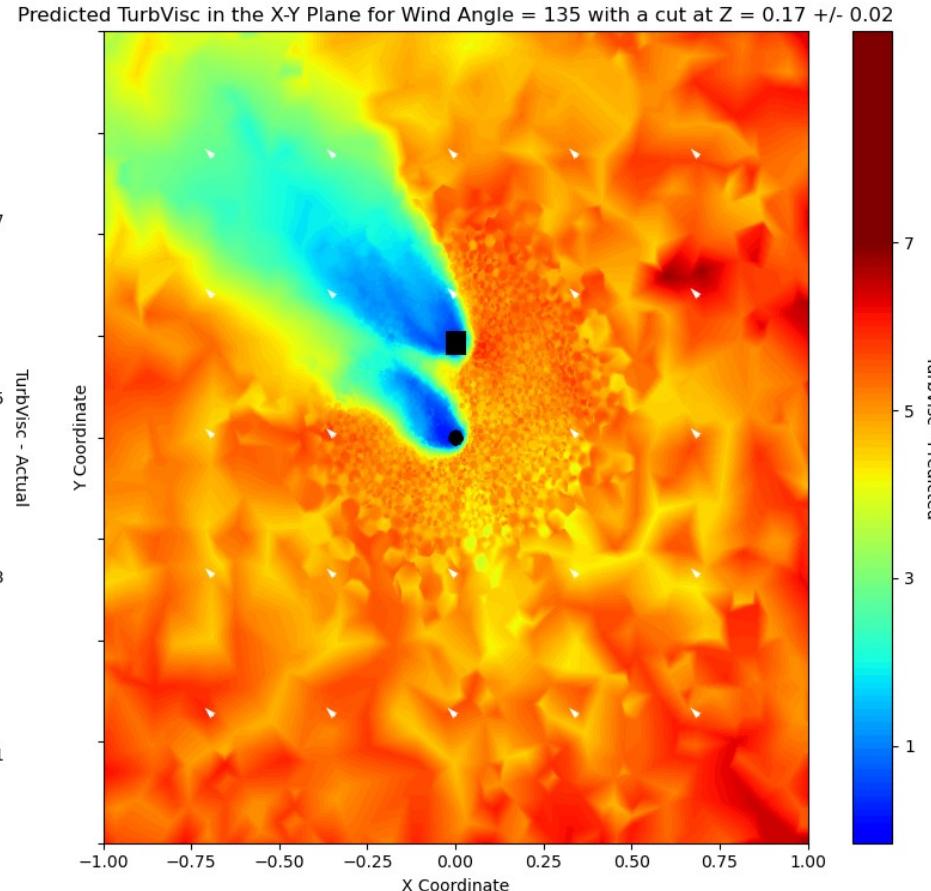
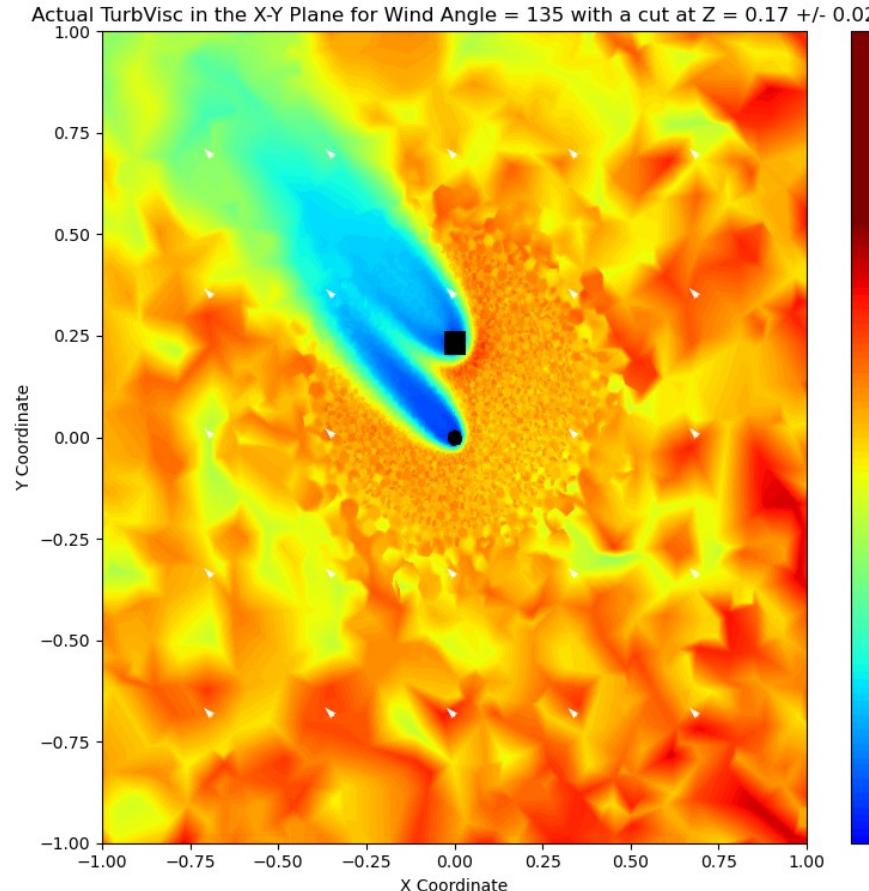


Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar), Threshold = 1E-5 (47325 Epochs, so far...), GPU Laptop
Predicting Results - X-Y Total Velocity Plot (Angle = 135)



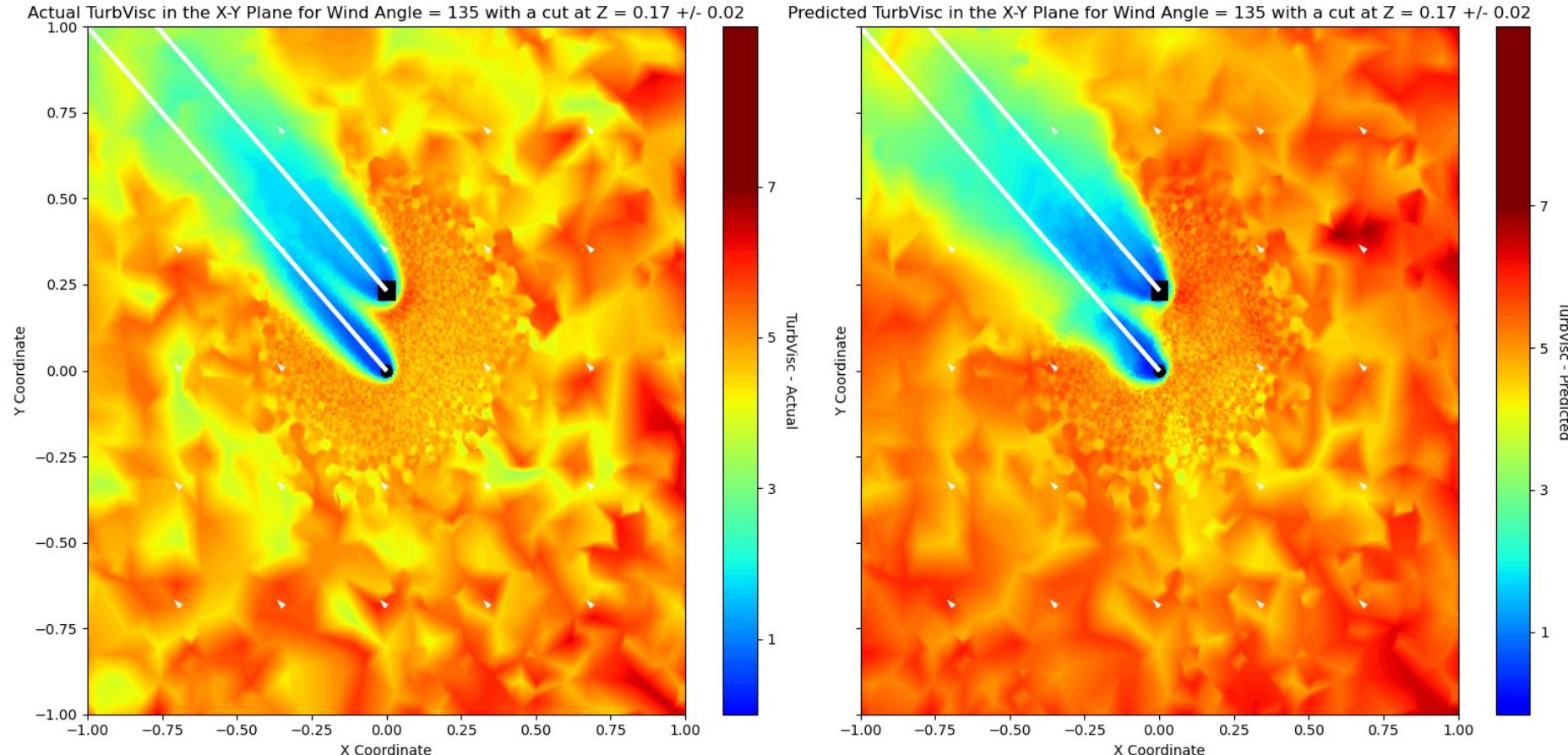
Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar), Threshold = 1E-5 (47325 Epochs, so far...), GPU Laptop
Predicting Results - X-Y TurbVisc Plot (Angle = 135)

Comparison of Actual vs. Predicted values with Wind Angle = 135 in the X-Y Plane with a cut at Z = 0.17 +/- 0.02

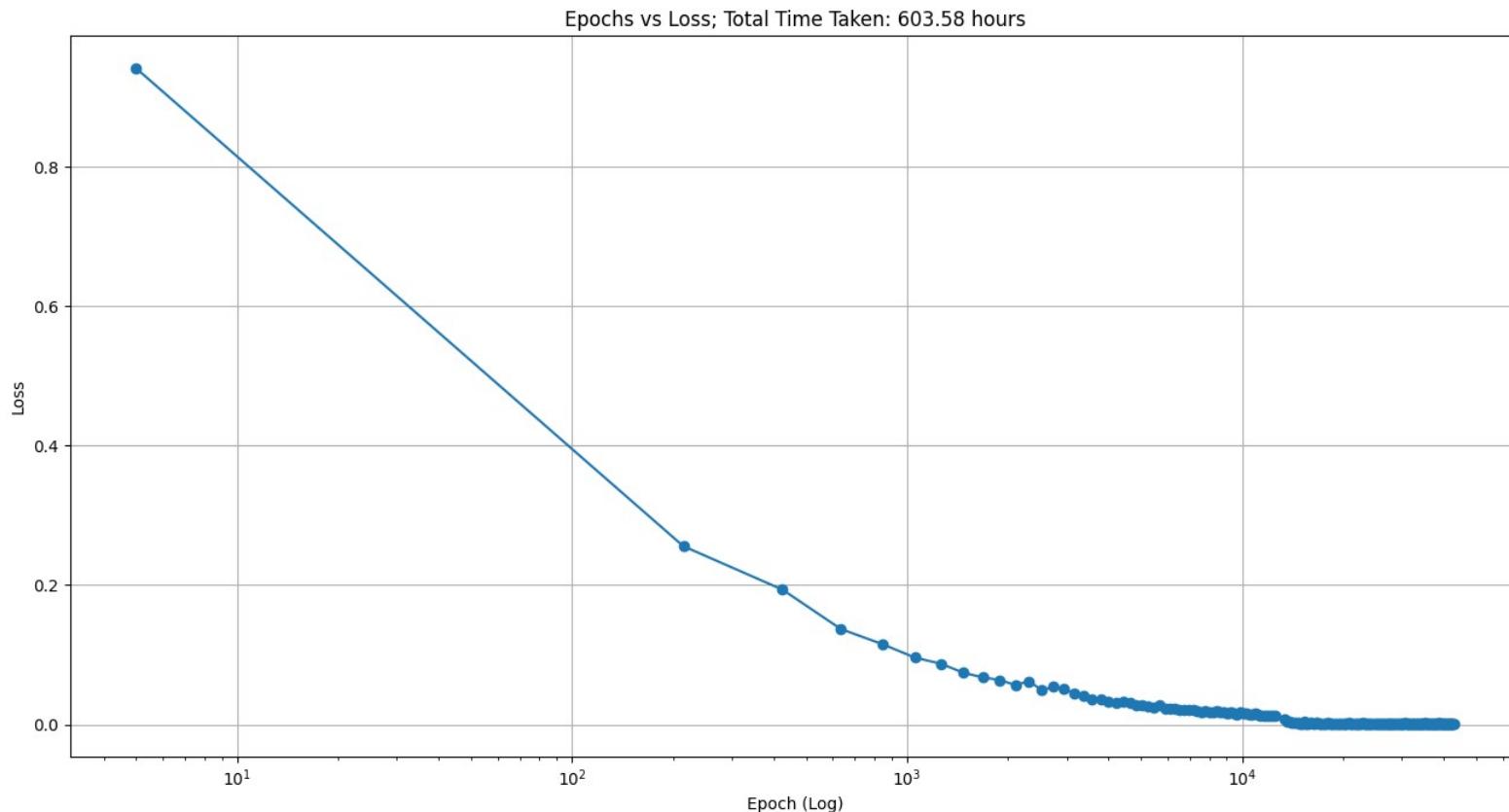


Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar), Threshold = 1E-5 (47325 Epochs, so far...), GPU Laptop
Predicting Results - X-Y TurbVisc Plot (Angle = 135)

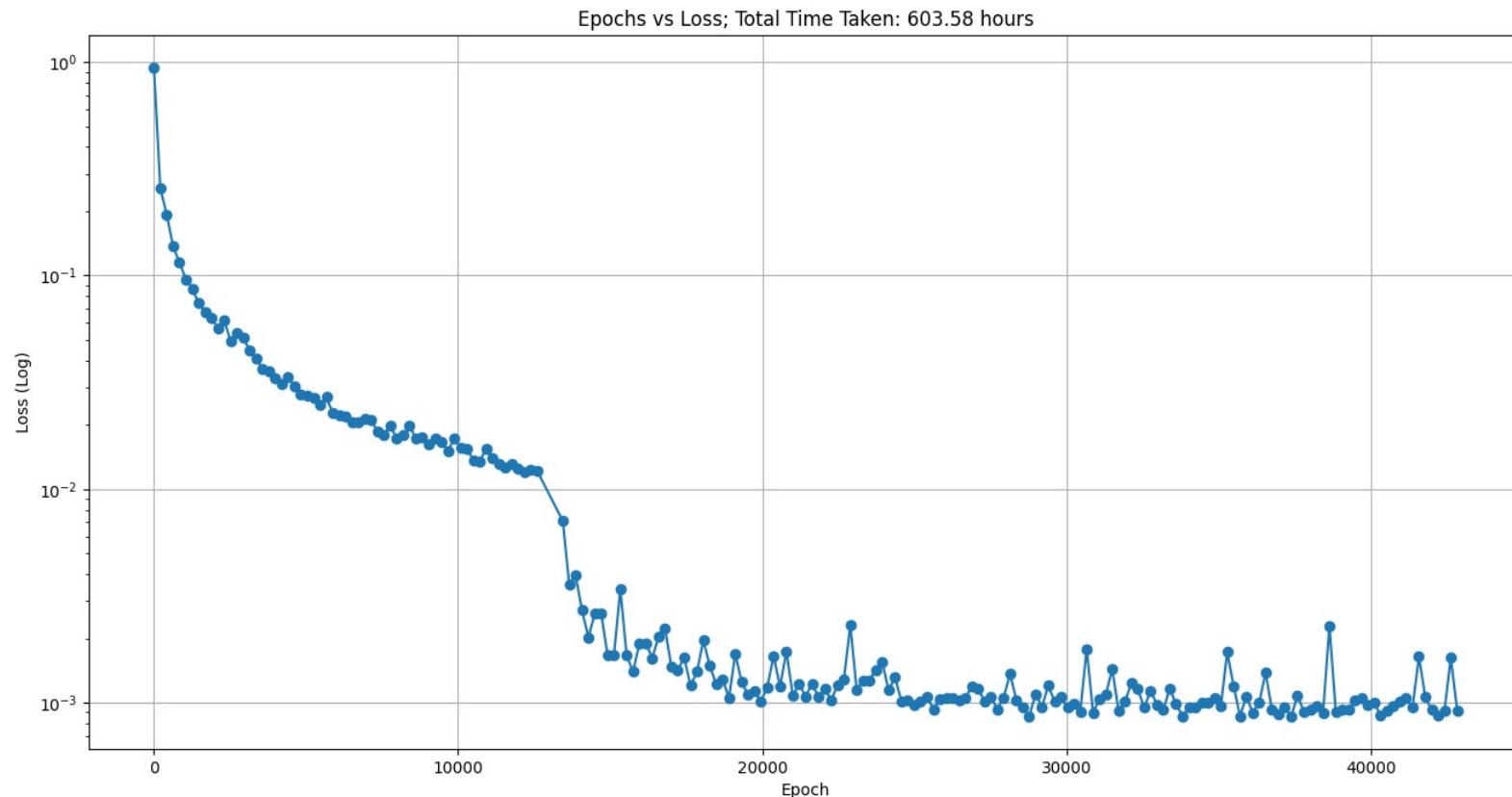
Comparison of Actual vs. Predicted values with Wind Angle = 135 in the X-Y Plane with a cut at Z = 0.17 +/- 0.02



Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar), Threshold = 1E-5 (47325 Epochs, so far...), GPU Laptop
Loss vs Epoch Plot



Progress so far - Data Loss Only (Adam Optimizer – Std Normal Scalar), Threshold = 1E-5 (47325 Epochs, so far...), GPU Laptop
Loss vs Epoch Plot



Progress so far - Data Loss + Cont Loss
(WITHOUT Boundary Conditions imposed)
(Adam Optimizer)

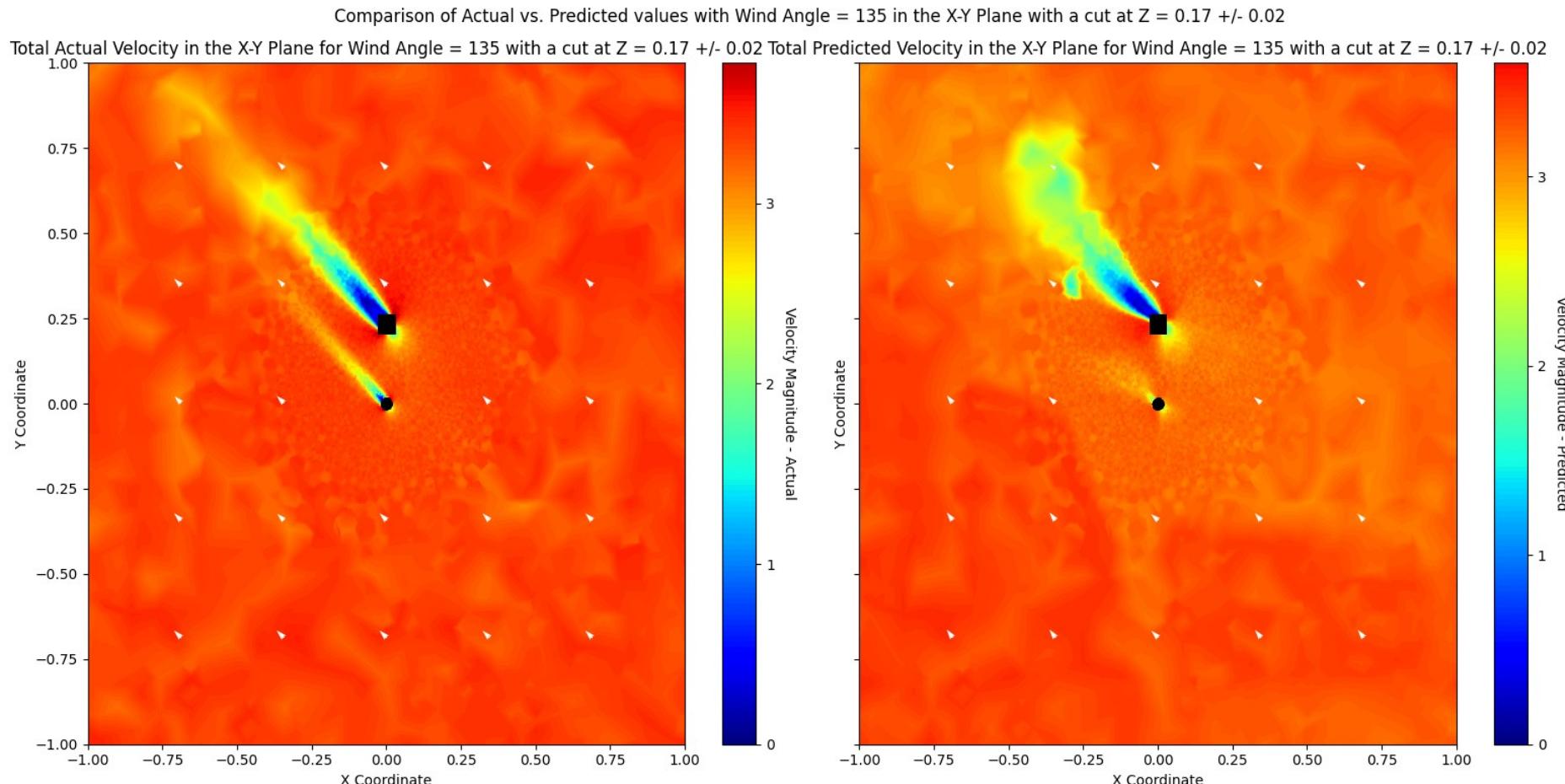
Threshold = 1E-5 (10610 Epochs, not completed), Google Colab

Scripts v3 – PREDICTING (135 DEG)

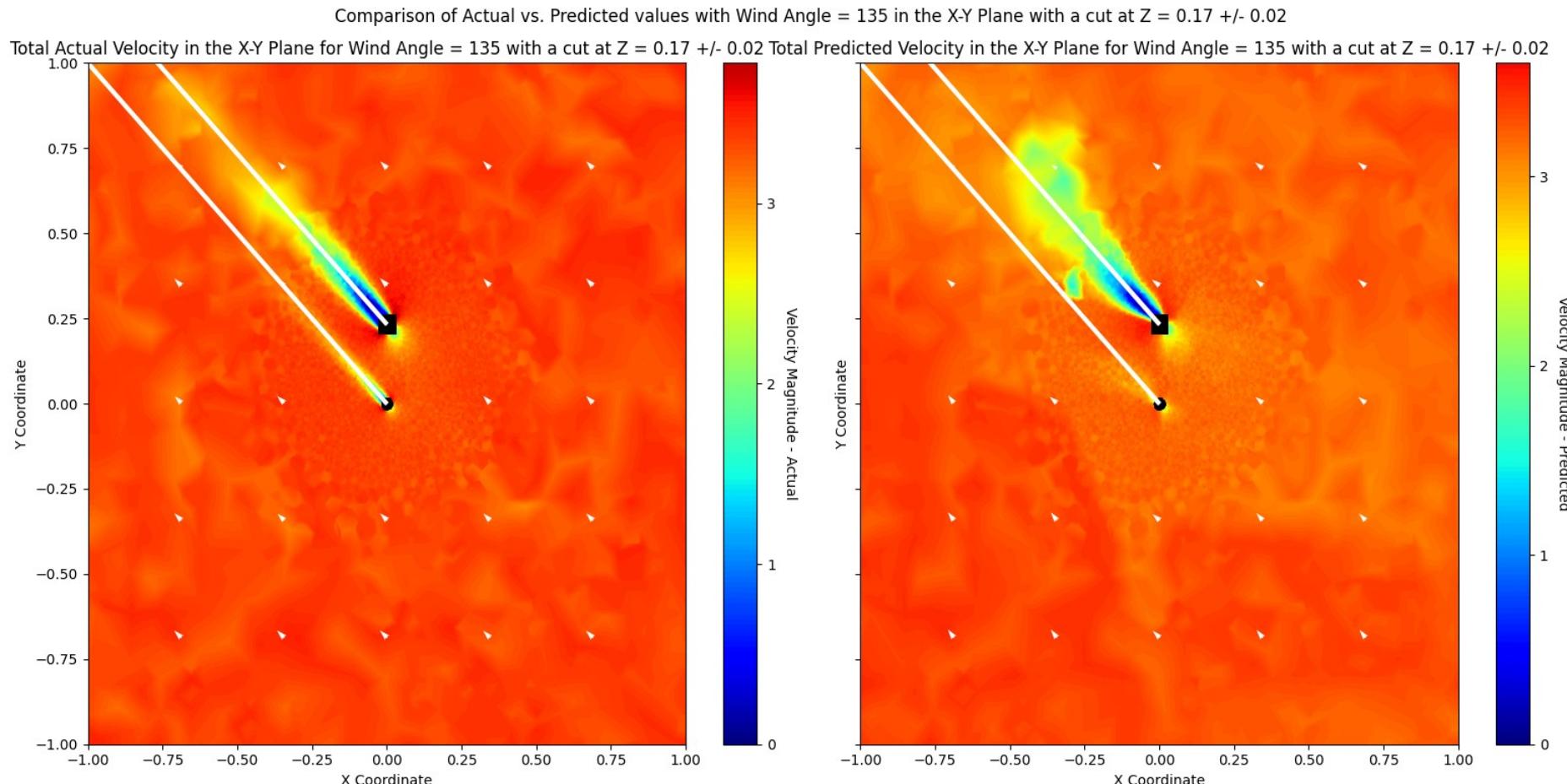
Progress so far - Data + Cont Loss (Adam Optimizer)
Threshold = 1E-5 (10610 Epochs, so far...), Google Colab
Predicting Results – Metrics (Angle = 135)

Variable	MSE	RMSE	MAE	R2
Pressure	0.685449654	0.827918869	0.528369796	0.594495436
Velocity:0	0.118347663	0.344016952	0.160197904	0.883884907
Velocity:1	0.144505396	0.380138654	0.194494929	0.859572314
Velocity:2	0.007320889	0.085562195	0.030433448	0.776215818
TurbVisc	0.327236887	0.572046228	0.431612503	0.997615436

Progress so far - Data + Cont Loss (Adam Optimizer), Threshold = 1E-5 (10610 Epochs, so far...), Google Colab
Predicting Results - X-Y Total Velocity Plot (Angle = 135)

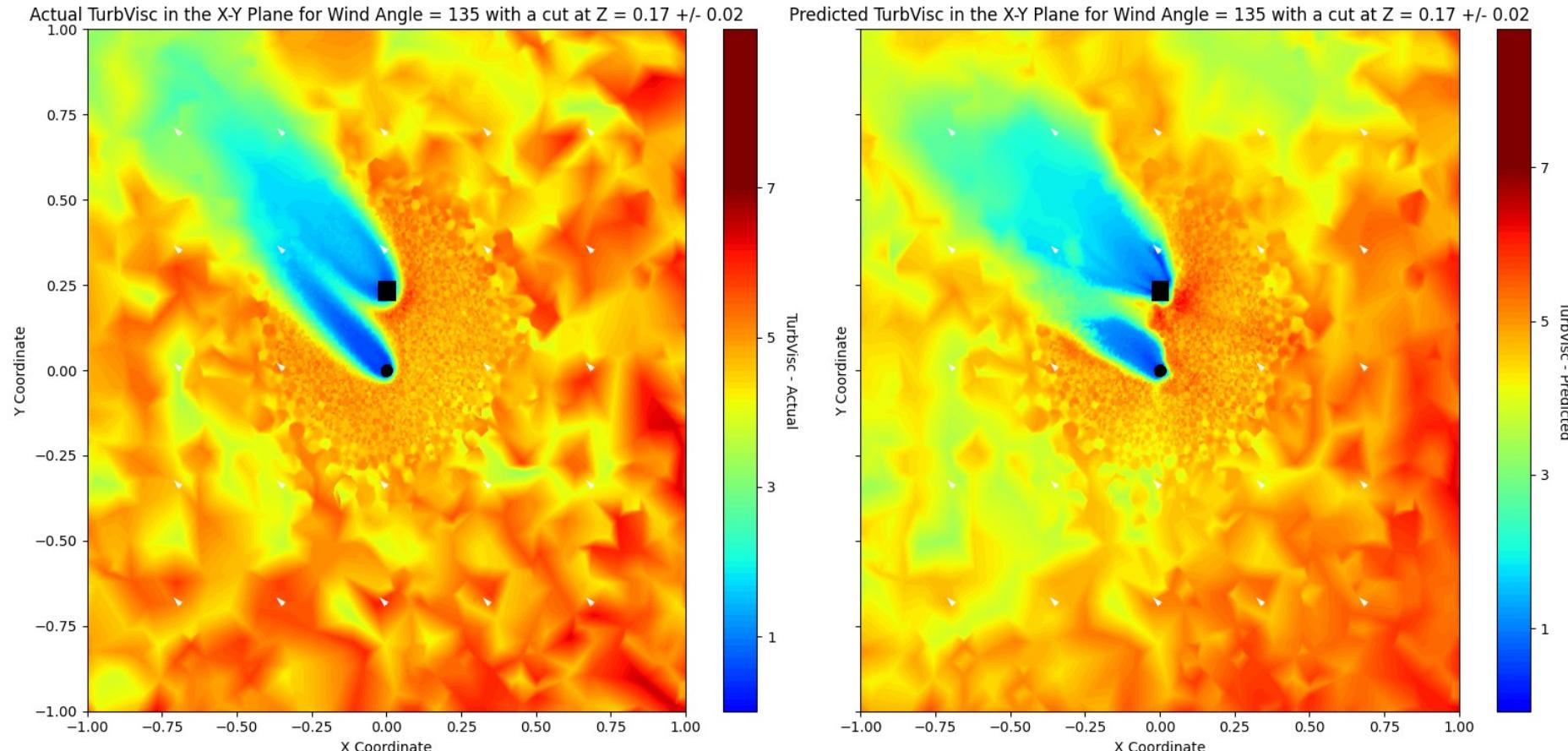


Progress so far - Data + Cont Loss (Adam Optimizer), Threshold = 1E-5 (10610 Epochs, so far...), Google Colab
Predicting Results - X-Y Total Velocity Plot (Angle = 135)



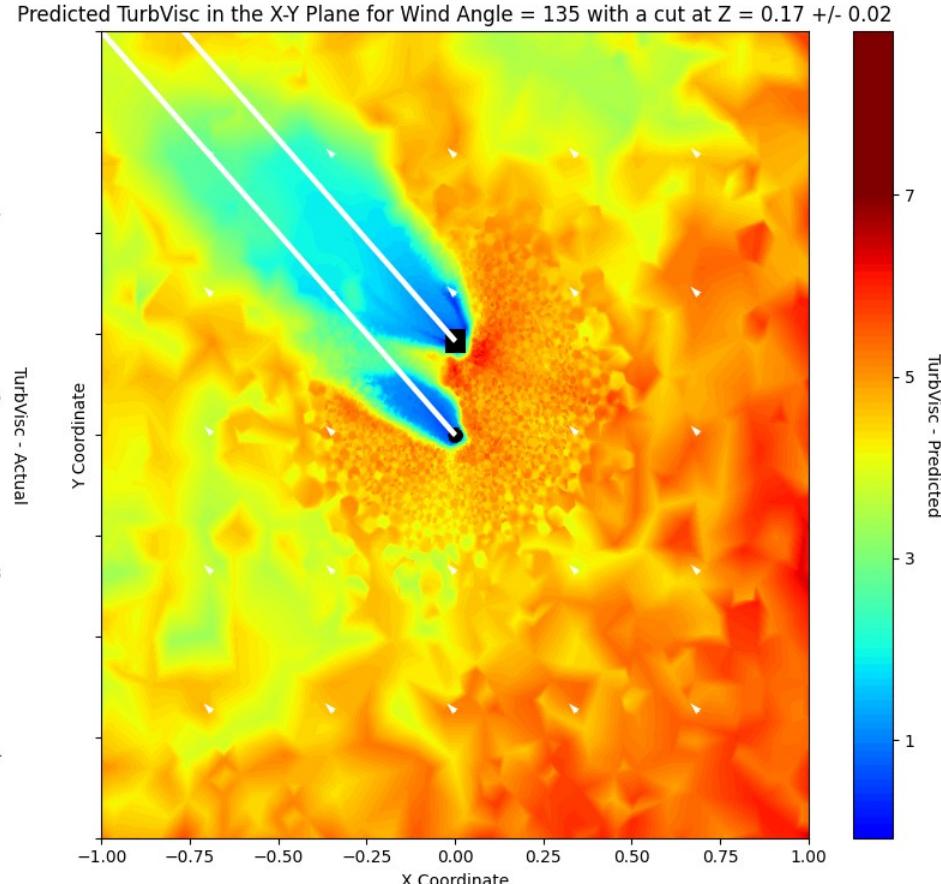
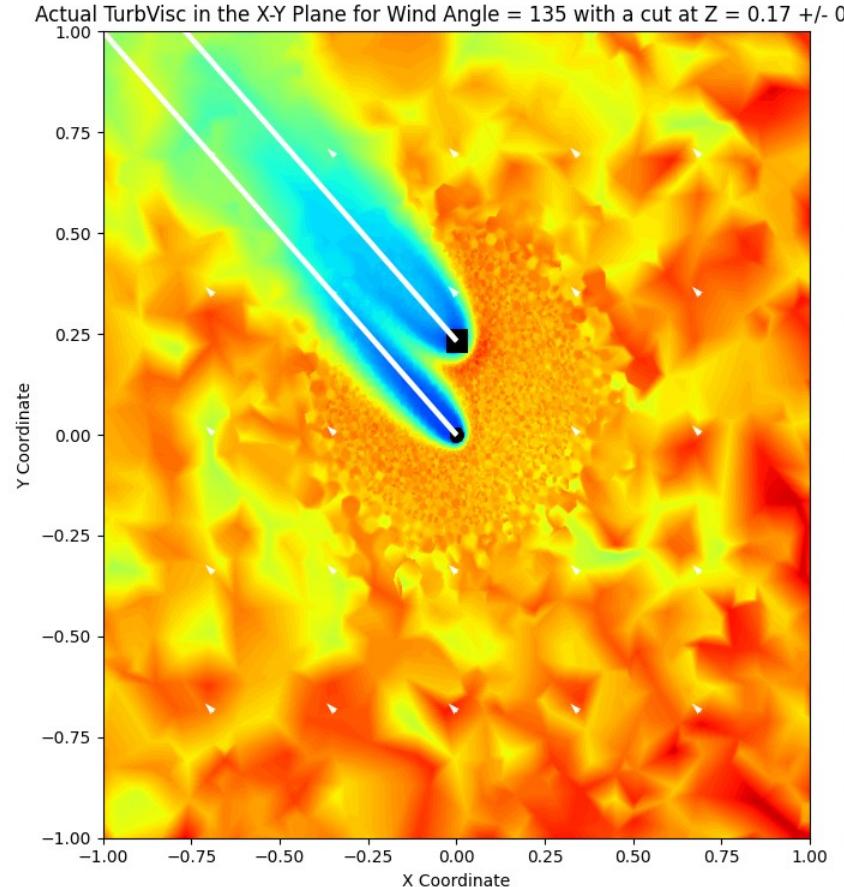
Progress so far - Data + Cont Loss (Adam Optimizer), Threshold = 1E-5 (10610 Epochs, so far...), Google Colab
Predicting Results - X-Y TurbVisc Plot (Angle = 135)

Comparison of Actual vs. Predicted values with Wind Angle = 135 in the X-Y Plane with a cut at Z = 0.17 +/- 0.02

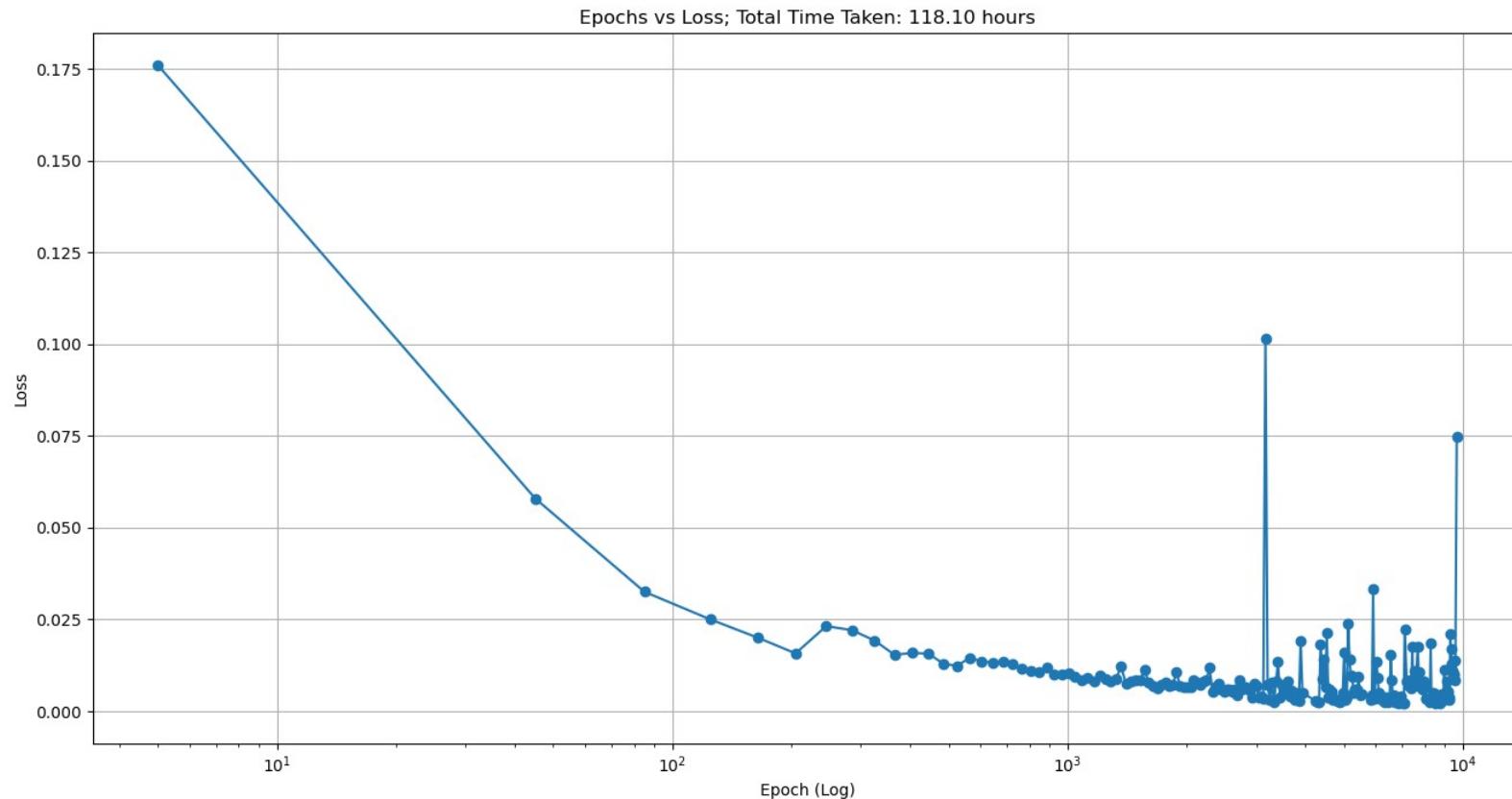


Progress so far - Data + Cont Loss (Adam Optimizer), Threshold = 1E-5 (10610 Epochs, so far...), Google Colab
Predicting Results - X-Y TurbVisc Plot (Angle = 135)

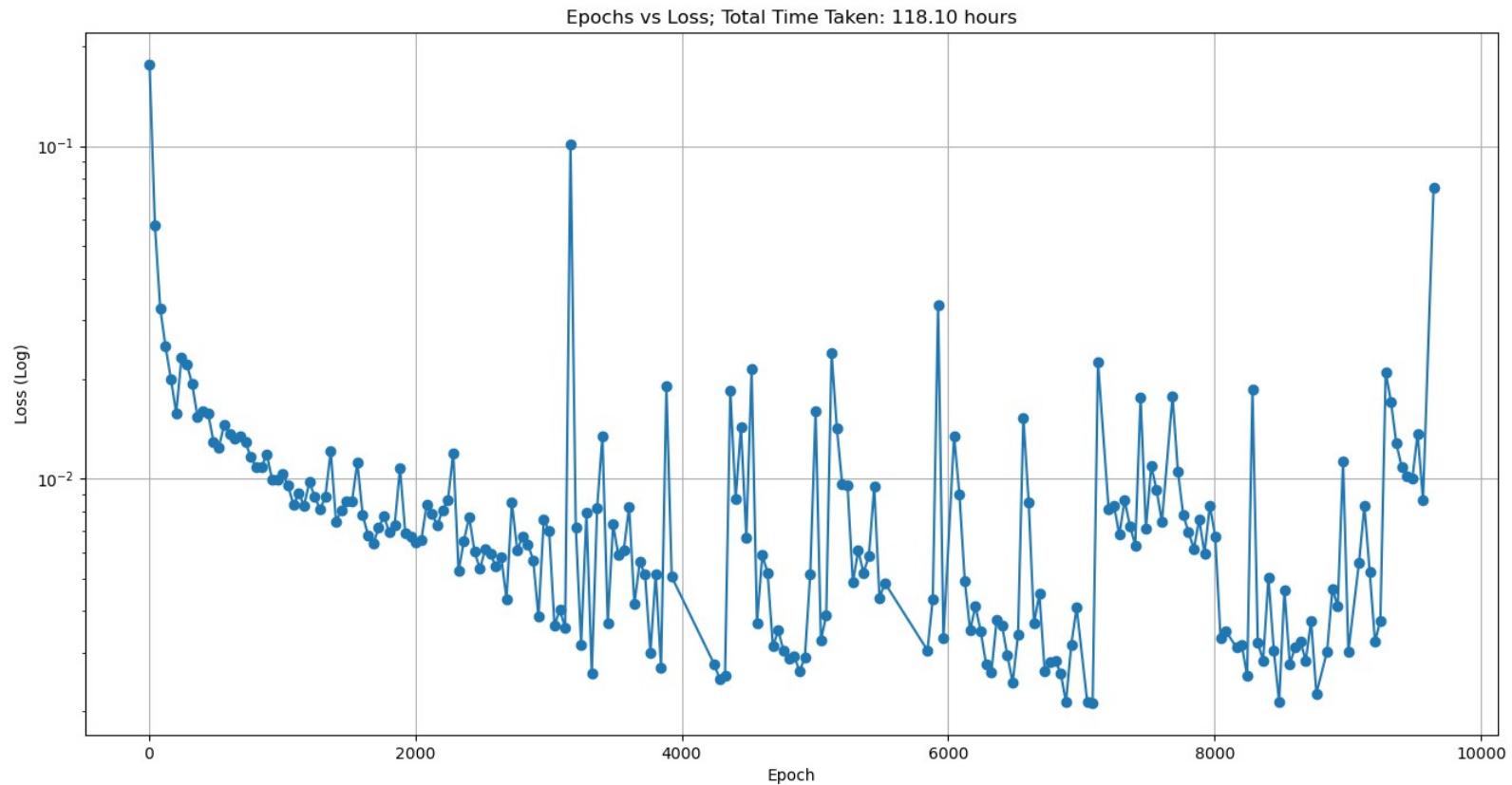
Comparison of Actual vs. Predicted values with Wind Angle = 135 in the X-Y Plane with a cut at Z = 0.17 +/- 0.02



Progress so far - Data + Cont Loss (Adam Optimizer), Threshold = 1E-5 (10610 Epochs, so far...), Google Colab
Epoch vs Loss



Progress so far - Data + Cont Loss (Adam Optimizer), Threshold = 1E-5 (10610 Epochs, so far...), Google Colab
Epoch vs Loss



Some Next Steps

Convert scripts for TPU use

Include inlet boundary conditions

TPU vs GPU

A TPU, or Tensor Processing Unit, is a type of application-specific integrated circuit (ASIC) developed by Google for neural network machine learning. It is specifically designed to accelerate machine learning tasks. Here are some key differences between a TPU and a GPU:

1. Design Purpose:

TPU: Optimized for machine learning and deep learning tasks.

GPU: Designed for graphics processing and rendering but has been adapted for parallel processing tasks, including machine learning.

2. Architecture:

TPU: Features a matrix processing unit for handling large amounts of matrix operations, which are common in deep learning.

GPU: Utilizes many small, efficient cores designed for handling multiple tasks simultaneously, suitable for both graphics and general parallel computing tasks.

3. Performance:

TPU: Highly efficient for specific tasks like neural network inference and training, offering high throughput for matrix calculations.

GPU: Offers versatile performance for a broader range of computing tasks, including but not limited to AI and machine learning.

TPU vs GPU

4. Flexibility:

TPU: More specialized and less flexible.

GPU: More flexible in terms of the variety of computations it can perform, useful in gaming, graphics, and general-purpose computing.

5. Integration and Accessibility:

TPU: More commonly found in cloud-based environments (like Google Cloud/CoLab) and less accessible for consumer-level usage.

GPU: Widely available for both consumer and enterprise use, with a broad range of applications beyond machine learning.

6. Software Compatibility:

TPU: Optimized for specific frameworks and may require specialized software to fully utilize its capabilities.

GPU: Compatible with a wide range of software and programming models, including CUDA for NVIDIA GPUs, making it more adaptable to various programming needs.

7. Cost and Availability:

TPU: Generally more expensive and less available to the average consumer, often accessed through cloud services.

GPU: More widely available and comes in a range of price points, from consumer-grade to high-end enterprise models.